multEvol: **An interactive pipeline for multitrait evolutionary analysis in a phylogenetic**

framework

Dipendra Nath Basu [1,*], Vaishali Bhaumik [1,*], Krushnamegh Kunte

National Centre for Biological Sciences, Tata Institute of Fundamental Research, GKVK

Campus, Bellary Road, Bangalore 560065, India

[1] These authors contributed equally

* Correspondence and email: Dipendra Nath Basu (dipendran@ncbs.res.in, +91 9535-699-

750), Vaishali Bhaumik (vaishali@ncbs.res.in, +91 9731-552-551)

ABSTRACT

Comparative phylogenetic studies based on 2D image data can reveal macroevolutionary patterns and processes by integrating phylogenetic and ecological analyses. The advent of high-throughput imaging facilities has led to the accumulation of large image datasets; however, large-scale data extraction and analysis using these resources can be labour- and computation-intensive. Moreover, there are few standardized methods to analyse multitrait image-based data in a phylogenetic framework. Several packages in the R statistical environment offer utilities for processing and analysing large-scale image data. Techniques for the comparative phylogenetic analysis of multitrait data have also been introduced in other packages. However, most of these approaches are specialized for discrete purposes, and there is a lack of streamlined and efficient methodological pipelines integrating features across packages. Here, we present *multEvol*, an interactive pipeline for the extraction and phylogenetic analysis of shape and colour pattern data from 2D images in the R statistical computing environment. Using this pipeline, shape outlines and colour pattern data for multiple colours can be extracted, visualised, and compared in a phylogenetic framework. Using various utilities provided in the *phytools*, *RNiftyReg*, *Momocs*, *patternize*, *convevol*, and *geiger* packages, we introduce an interactive interface that allows user inputs for iterative data extraction. This pipeline provides an efficient method for the bulk processing of images of biological specimens from museum collections. As such, it has potential applications in the large-scale morphometric analysis of museum specimens to reveal macroevolutionary patterns in ecology, evolution and integrative biology.

Keywords: Colour pattern, elliptic Fourier analysis, multitrait evolution, phylogenetic analysis, convergence, rate of evolution

INTRODUCTION

Earth's biodiversity is marked by spectacular morphological evolution and diversification of species. Species diversification typically involves evolution along multiple trait axes, which helps organisms adapt to their natural environments and occupy new niches. Comprehensive macroevolutionary analyses of these traits has long posed a challenge to biologists. Quantifying the degree, direction, and rate of morphological change can help elucidate macro- and micro-evolutionary processes in biological systems. However, comparative studies in ecology are frequently limited by a lack of standardized methodology for data extraction and processing [1,2], especially in the bulk analysis of data within a phylogenetic framework. The extracted data may also need to be summarized or otherwise re-structured for use in phylogenetic and statistical analyses, and the methodologies for these are not readily apparent or easily available.

The extraction of shape and colour pattern data from 2D images—such as images of insect wings or plant leaves—offers a versatile means of data collection using relatively inexpensive resources. Comparative studies on diverse taxa, such as bats [3] and butterflies [4], have used shape analysis to examine the evolutionary history and functional constraints of morphological features. Wing colours and colour patterns are extremely diverse and play important roles in mimicry [5], mate recognition [6] and thermoregulation [7], along with other adaptive functions. However, comparative studies on the evolution of complex traits usually focus on relatively closely related species [3,8,9], which may limit the utility of these methods in comparisons across study systems. In addition, standard methods for phylogenetic analysis are typically designed to address specific questions and are incompatible with image data. Therefore, it is important to develop a systematic and interactive pipeline that extracts preliminary data from images and transforms them into phylogenetically corrected formats that are usable for comparative analysis across distantly related taxa.

Here, we present *multEvol*, a pipeline for data extraction from 2D images and phylogenetic analysis of morphological data (Fig. 1) in the R statistical computing environment [10]. The extraction of shape data mostly depends on the *momocs* package [11], which is a dedicated tool for shape analysis in R. The extraction of colour pattern data primarily uses the *patternize* package [12], which allows pattern extraction at the pixel level using a user-defined RGB threshold. In both cases, we have created functions that allow user interaction, which can help ensure proper alignment, harmonic calibration (for shape), and pixel-level pattern selection (for colour) between multiple samples. The outputs can be transformed using phylogenetic principal component analysis (pPCA, package *phytools* [13]), and the PCs can be used for further statistical or phylogenetic

analysis, such as estimating the degree of convergence (package *convevol* [14]) or rate of evolution

(package *RRphylo* [15]). We demonstrate the utilization of this pipeline using 2D wing images of

butterflies. The pipeline can also be used to analyse any continuous variables—such as

morphometric data—that have been extracted using other methods.

METHODS

Data extraction

*Outline shape***:** In geometric morphometric analyses, biological shapes are estimated through two

major approaches: landmark-based analysis and outline analysis. Although both methods retain the

relative geometric information of the shapes [16,17], coordinate homology is an essential

prerequisite in the landmark method [18]. However, homologous landmarks may not be available

in all biological samples, which restricts the utilization of this approach. Additionally, landmarking

on the homologous points is a time-consuming process. In contrast, elliptical Fourier analysis

(EFA) [17,19,20] is a robust, resource-efficient, and time-efficient method of outline analysis that

accurately quantifies 2D closed contours. Unlike other Fourier-based methods, EFA can operate on

virtually any shape, including ones that lack positions for homologous landmarks [20].

Contemporary studies on geometric morphometrics are increasingly using EFA to estimate 2D

biological shapes [21].

In the EFA approach, the x and y coordinates of closed contours are extracted from the

binary images. These outlines are smoothened to a small factor to account for biological

aberrations, following which they are centred, aligned, and scaled to remove allometric signals

(Fig. 2a). The outlines are size-corrected based on the centroid size. Outline coordinates for each

specimen are resampled to introduce homology, and a Procrustes fit is performed on these

homologous outline coordinates for better alignment. Resetting the first coordinate of each outline

further standardizes the contour estimates. A suitable number of harmonic ranks (a series of

ellipses) are then estimated based on the meanshape of the aligned contours (Fig. 2b). Each contour

is then represented as a series of calibrated elliptical harmonics (Fig. 2c). These ellipses are defined

as the sum of one sine and one cosine curve by decomposing a periodic continuous function

implementing an extension of the Fourier series (Fig. 2d). Fourier transformation calculates four

coefficients for each harmonic, which are eventually normalized based on the first harmonic to

remove the effect of size and rotational variations [17]. These normalized elliptical Fourier

descriptors (EFDs) are used as shape variables for further analysis. We implemented a user-friendly

interactive function 'cleqEFA()' based on utilities provided in R package *Momocs* for outline

extraction, alignment, and transformation techniques [11,22].

Colour pattern: Colour pattern is a complex trait with multiple quantifiable dimensions. Colour

pattern data can be quantified in various ways, including relative linear measurements or areas

occupied by a particular colour range [23,24] or estimating the shape variance of homologous

colour patches across multiple surface [25]. These linear and geometric data can be stored in a

presence-absence matrix for each range of colour values (RGB values) on appropriately aligned

surfaces. Therefore, this method of pattern extraction makes the data comparable across variable

and large image datasets, and can be used for further analysis. The accuracy of these data depends

on two components: an efficient image registration approach to introduce homology between

samples, and appropriate colour thresholding to extract the spatial and geometric information of

homologous patches.

Images can be superimposed to obtain homology through two main approaches: image

registration and landmark-based homology. Biological specimens often lack homologous

anatomical positions, which restricts the use of landmark-based approaches. Therefore, to obtain

homology in a computationally efficient manner, we have opted for a two-step image

transformation. In the first step, a binary image template is prepared based on either the meanshape

of the 2D surfaces containing colour patterns, or any surface with close resemblance to the

meanshape. Subsequently, one specimen of each taxon or species is affine-transformed onto this

binary template to obtain a taxon- or species-specific template. In the second step, these templates

are used to register all the images using an image registration approach based on similarity of colour

intensity (Fig. 1b). The affine transformations are performed iteratively approach using the utilities

of the R package *RNiftyReg* [26].

Following image registration, the colour patches that are homologous across multiple

surfaces are isolated through thresholding. Most unsupervised thresholding approaches are limited

to systems with binary or conspicuous colour patterns (that is, systems in which the surfaces have

distinct background and foreground colours), and are not very efficient in systems with multiple

colours or continuous colour boundaries. This pipeline uses a supervised RGB thresholding

approach where colour boundaries are defined by iteratively sampling from a representative

specimen for each species. This approach efficiently extracts colour patterns as raster layer objects

for each selected colour range. These raster layers are then converted to binary presence–absence

matrices and used for subsequent analyses. RGB thresholding and raster layer extraction are

performed using utilities in the R package *patternize* [12].

Phylogenetic analysis

Phylogenetic PCA and size-correction: Most statistical analyses assume that the data have been

collected from independent samples. However, this assumption does not hold during data analysis

in a phylogenetic framework. Comparative phylogenetic analyses that involve statistical

transformation of continuous morphological variables for the estimation of phylogenetic signal or

ancestral state reconstruction may require phylogenetic corrections [27]. Statistical comparisons

without preliminary phylogenetic corrections show higher variance and are prone to type I error.

Hence, this pipeline includes a phylogenetic PCA and offers the option of size correction against

body size, as implemented in the R package *phytools* [13].

Mode of evolution: Several analytical methods have been developed to estimate non-neutral trends

of trait evolution in a phylogenetic framework [9,28]. Estimating these model parameters can reveal

the effects of selection and constraints on trait evolution. The 'pcModels()' function uses utilities

provided in the R packages *APE* [29], *phytools* [13], and *geiger* [30] to fit a phylogenetic tree with

a user-defined number of principal components (PCs) and obtain the best fit model. To estimate

the extent of convergence in trait evolution, the *convevol* package is used to calculate four

convergence indices (C1–C4) [28], which are Euclidean distance-based estimates of convergence

among groups of species on a phylomorphospace. Among the various C metrics that can be

calculated, C1 denotes the relative convergence in each trait between a group of species, and is

comparable across datasets. The *convevol* package also provides a way to simulate data using

Brownian motion model parameters to evaluate the significance of the convergence.

Rate estimation: Comparative phylogenetic analyses often require estimates of the rate of change

in phenotypes across evolutionary time. The rate of trait evolution depends on ancestral state

reconstruction, which can be performed in two ways: 1) ancestral state reconstruction following a

macroevolutionary model (single- or variable-rate models) within a well sampled clade or closely

related clades; and 2) regression-based estimation. A regression-based method is computationally

more efficient than Bayesian approaches and can accurately predict the ancestral characters of

species belonging to distant clades. The *multEvol* pipeline implements the ridge regression method

in the *RRphylo* package [15] to estimate the rate of trait evolution of multiple traits using PCs

obtained from the preliminary analysis (Fig. 1c).

OUTPUT

The main *multEvol* functions for shape extraction take images as input; extract, scale, and align the

outlines; and perform elliptical Fourier analysis on those shapes. The output of the 'cleqEFA()'

function is a list containing the EFDs as a 'coe' object, as well as the estimated mean outline for

each species as a 'coo' object (*Momocs*). The 'shpComp()' function extracts the deformation

isolines among the meanshapes of different species for comparative visualization. The 'colData()'

function for colour pattern extraction performs RGB thresholding on images using iterative user

inputs in an interactive manner to obtain binary matrices as outputs from each raster object

(*patternize*). These matrices are eventually transformed into a proportional matrix for each colour

range for each species. The 'colData()' function also stores the raster layer objects for each colour

range in .png format as confirmation for efficient registration and thresholding, as well as a list of

the user-selected RGB value and threshold for each sample. The 'concat()' function concatenates

the linearized proportional matrices of different colour ranges. The 'colComp()' function sums the

RasterStacks to visualize the heatmaps of intra- and inter-species colour pattern variation in a

comparative manner. The EFDs from outlines, species-level proportional colour pattern data, and

any phylogenetically size-corrected continuous multivariate datasets can be subjected to

phylogenetic PCA using a phylogenetic tree. The results of phylogenetic PCA are used to visualise

inter-species variations in trait space, and the PC scores are stored for further analysis. The

'dataPrep()' function fits six macroevolutionary models (Brownian motion [BM], early burst [EB],

Ornstein-Uhlenbeck [OU], lambda, kappa, and delta) to the PCs of each trait and stores the AICc

values for each model. The 'cIndex()' function estimates and stores convergence metrics for each

user-defined group of species (regimes) and calculates their significance based on simulations using

a BM model. The rate of trait evolution is estimated by the 'rateEvol()' function based on the user-

defined number of PCs and a phylogenetic tree. This function stores the evolutionary rate for each

branch of the phylogeny in a data frame, which can be used to plot a heatmap cladogram.

EXAMPLE

Study system: In biological systems, mimicry occurs when a palatable or relatively undefended

prey species evolves resemblance to a well-defended (aposematic) species, experiencing reduced

predation pressure and deriving a fitness benefit. Aposematic species that resemble each other in a

mutualistic interaction are known as Müllerian co-mimics, whereas palatable species that mimic a
toxic model in a parasitic interaction are known as Batesian mimics. In this example, we define a
mimicry ring as a community that contains at least one well defended aposematic species (Batesian
model) and at least one palatable species (Batesian mimic) that resembles the model [31].

Butterflies in a mimicry ring show varying degrees of phenotypic convergence in multiple
traits, including colour [32] and colour pattern signals [5,33] as well as locomotor cues [34]. These
traits may evolve under different models of selection and at varying rates within and between
species [4,23]. The *Tirumala* mimicry ring endemic to the Western Ghats biodiversity hotspot in
India consists of five unpalatable models with a shared phenotype and shared ancestry, and three
distantly related palatable species (Batesian mimics) that have evolved to resemble the toxic models
(Fig. 3) [31,35]. The mimics comprise two species of female-limited mimics (*Pareronia hippia* and
P. ceylanica), where the males are non-mimetic, and one species of sexually monomorphic mimic
(*Papilio clytia* f. *dissimilis*) where both sexes share the mimetic phenotype. Here, we examine the
evolution of wing shape and colour patterns in this mimicry ring using the *multEvol* pipeline to
demonstrate its utility in investigating the evolution of multiple traits under various degrees of
mimetic selection. For phylogenetic analyses, we first prepared a time-calibrated phylogeny
consisting of the models, mimics, and some of their respective sister species. We then extracted
wing shape and colour data from the forewing images of all species and estimated the degree of
convergence between models and mimics, as well as the rate of evolution of the two traits, as
described above.

Data extraction and preliminary analysis: Using digital SLR cameras and lenses, we
photographed one forewing (dorsal surface) of each specimen and extracted the wing shape and
colour pattern data. Images were captured under a uniform camera flash units because variation in
colour tones under different light conditions may produce different results. We extracted shape data
from 265 images using the 'cleqEFA()' function, and colour data from 200 images using the
'colData()' function. Seven harmonic ranks were calibrated to explain the outlines with 99%
accuracy (Fig. 2b). The EFDs from these seven harmonics were normalized against those of the
first harmonics, resulting in six remaining EFDs. Data were extracted for three colour ranges—
melanistic (including black and brown), red/orange, and blue/green—with a resampling factor of
three, and the resulting proportional matrices for each colour range were linearized and

concatenated for each species. The EFD datasets and concatenated colour pattern data were used

for a phylogenetic PCA, and six evolutionary models were fit to the resulting PCs.

RESULTS

The first two PCs explained 96.23% and 98.1% of the variance in shape and colour pattern data,

respectively. Of the six models compared, the lambda model of evolution had the highest support

for the first two of shape (AICc values: PC1, -83.21; PC2, -110.51) and color (AICc values: PC1,

228.76; PC2, 174.03). The meanshapes of each model and mimic species were reconstructed from

their respective EFDs. For each model–mimic pair, the shape changes were visualized as

deformation isolines between the meanshapes of each species (Fig. 4a). In contrast to sexually

monomorphic mimics and mimetic females of female-limited mimics, the non-mimetic males

showed multiple local deformations (red areas in Fig. 4a). The summed raster layers were plotted

as heatmaps to visualise intra-species colour variation (that is, variation in colour patterns between

samples of a single species; plots along the top and left margins in Fig. 5a). Pairwise differences in

the species-level proportional raster layers were plotted as heatmaps to indicate inter-species

differences in colour patterns between each model–mimic pair (Fig. 5a). Similar to the trend

observed in wing shapes, non-mimetic males showed more differences in colour patches compared

to models, whereas sexually monomorphic and female-limited mimics were similar to models. The

phylomorphospaces for shape and colour pattern analysis indicated an overlap between models and

mimics (Figs. 4b and 5b). In contrast to mimetic females, the non-mimetic males of female-limited

mimetic species were relatively distant from the traitspace occupied by models and mimics. The

convergence indices of various species combinations (only Batesian mimics, only aposematics,

sexually monomorphic mimics + aposematics, and female-limited mimics + aposematics) were

plotted using the shape and colour pattern data to visualize the distribution of C1 values in 100

simulated datasets (Fig. 6a). There was significant convergence in wing shape and colour patterns

within models and between models and female-limited mimics, as well as in wing shape between

models and sexually monomorphic mimics (star symbols in Fig. 6a). The evolutionary rates of wing

shape and colour pattern were plotted onto heatmap cladograms, which showed that lineages

containing models or mimics generally evolved faster (Fig. 6b).

CONCLUSION AND RECOMMENDATIONS

The *multEvol* pipeline can be used to compare the distribution of colour ranges across species, and

the interactive features allow the iterative selection of appropriate harmonics, RGB values, and

colour pattern matrices across multiple samples. This is especially useful for large-scale supervised
data collection from museum collections or field-collected specimens. Museum collections
worldwide represent a vast resource of historical DNA; however, preserved specimens have limited
applicability as sources of biological tissue. As such, the systematic photographing and cataloguing
of museum specimens can improve their long-term usefulness as sources of morphological data
[4,36]. The utilization of museum specimens alleviates several taxonomical and logistical
limitations [37,38] and enables the testing of various macroevolutionary hypotheses. The pipeline
presented here provides the potential for such large-scale comparative analyses, and we hope that
the methods described and pipeline presented here will prove useful to researchers studying shape
and colour pattern variation in biological systems.

Author Contributions: DNB and VB conceptualised the analytical pipeline, developed the code,
and conceptualised and performed phylogenetic analyses. KK conceived the broad research
questions, supervised the research, and contributed specimens for image analysis. DNB and VB
wrote the manuscript with inputs from KK.

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Data availability: The functions and their descriptions are available on GitHub
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Figure 1: Data extraction, outputs, and potential statistical analyses of shape and colour data

using the *multEvol* pipeline. Butterfly wings are photographed and converted into binary images

for the extraction of shape (a) or colour pattern (b) data. The 2D shapes are scaled, aligned across

all images, and Fourier transformed to obtain the mean descriptors for each species or group. The

colour data comprise proportional matrices for multiple colours, where each matrix indicates the

pixels that contain the specified colour (0 = none of the images sampled contain the specified colour

in that pixel; 1 = all images sampled contain the specified colour in that pixel). The matrices are

linearized and used for further analysis, which may include a phylogenetic principal component

analysis (PCA) and estimation of convergence or rate of evolution.

Figure 2: Data processing and extraction of elliptical Fourier descriptors for shape outlines using the 'cleqEFA()' function. (a) The right forewings (n=265) of butterflies in the *Tirumala* mimicry ring are binarized, and their outline coordinates are extracted. These outlines are scaled and aligned, and the start points of the contours are reset to obtain the final stack of outlines. **(b)** Harmonic power plateaus after the seventh harmonic. **(c)** The harmonic ranks are calibrated to obtain an accurate representation of the outlines. The coordinates of 12 randomly selected equidistant points on the wing contours are plotted directionally to observe the periodic decomposition of the sine and cosine curves from an outline. **(d)** The harmonic sum of a series of fitted ellipses (n=7) on the wing outline—where the higher order ellipse follows the periphery of the lower order ellipse—is Fourier transformed to obtain elliptical Fourier descriptors.

Figure 3: Müllerian co-mimics and Batesian mimics in the *Tirumala* mimicry ring of the Western Ghats, India. The five Müllerian co-mimics (red arrows) have shared ancestry and act as Batesian models for the Batesian mimics (blue arrows), which are distantly related. *Pareronia* spp. are female-limited mimics, where the females mimic the models and the males are non-mimetic.

Figure 4: Inter-species variation in wing shape among mimetic butterflies. (a) Pairwise comparisons of deformation isolines (scale: blue=low deformation, yellow=moderate deformation, red=high deformation), showing the changes in wing shape in model–mimic species pairs in the *Tirumala* mimicry ring. **(b)** A morphospace plot based on the phylogenetic principal component analysis of shape descriptors, showing the relative positions of aposematics (red), mimics (dark blue), and non-mimetic males of female-limited mimics (light blue) in the traitspace.

Figure 5: Intra- and inter-species variation in wing colour patterns among mimetic butterflies. **(a)** Heatmaps along the top and left margins show intra-species variations in colour patterns, and the remaining heatmaps exhibit inter-species differences in colour patterns in model–mimic species pairs in the *Tirumala* mimicry ring. The heatmap scale is shown at the bottom right. **(b)** A morphospace plot based on the phylogenetic PCA of colour pattern data, showing the relative positions of aposematics (red), mimics (dark blue), and non-mimetic males of female-limited mimics (light blue) in the traitspace.

 Figure 6: Evolutionary characteristics of forewing shape and forewing dorsal colour patterns

 in the *Tirumala* mimicry ring. (a) Convergence among Batesian mimics (distantly related

 palatable species; includes female-limited dimorphic and sexually monomorphic mimics); among

 aposematics (toxic species with similar colour patterns); between aposematics and female-limited

 dimorphic mimics; and between aposematics and sexually monomorphic mimics. C1 values (red:

 actual C1; black: mean C1 across 100 simulations) are shown for forewing shape (left) and

 forewing dorsal colour patterns (right). A star indicates significant convergence relative to the

 convergence estimates from 100 simulations. **(b)** Rates of evolution of forewing shape and

 forewing dorsal colour patterns. Colour coding for species names indicates aposematics (red),

 Batesian mimics (dark blue), and the males of female-limited Batesian mimics (light blue).

Museum specimen photograph → **Extracted resized porion of image (resized)**

a

Conversion to binary image → Extracted 2D closed contours → Scaling and aligning

Input: No of harmonics → *Fourier transform*

Fitting harmonics estimating meanshape outlines

Fourier descriptors for all the shape outlines

Descriptors for mean shape of each species

b

2D registration on a binary target (affine transform)

Input: RGB values for blue → *RGB values for black* → Colour thresholding (each colour, each specimen) → Rasterstack & binary matrix extraction (each colour, each specimen)

Proportional matrix (each colour, each species)

Any continuous multivariate data

Phylogenetic correction/ standardization

Phylogenetic PCA

c

Convergence

Multi trait comparisons

Comparison of convergence (Mode of trait evolution)

C1 convergence index (Stayton, 2015)

Ridged regression

Trait A   Trait B

Heatmapped cladograms (Rate of trait evolution)

Phylomorphospace

Phylogeny

Pipelines: ▮ a. Shape trait extraction ▮ b. Colour pattern trait extraction ▮ c. Phylogenetic comparisons

a Contour alignment

b Harmonic power

c Elliptical analysis

d Harmonic estimates

Tirumala limniace ♂♀

Tirumala septentrionis ♂♀

Pareronia ceylanica ♀ ♂

Parantica aglea ♂♀

Parantica nilgiriensis ♂♀

Pareronia hippia ♀ ♂

Idea malabarica ♂♀

Papilio clytia f. dissimilis ♂♀

Batesian model and Müllerian co-mimic

Batesian mimic

←→ Müllerian co-mimics   •→ Aposematic species   →→ Batesian mimics

•→ Batesian mimics   ⇌ Intersexual genetic correlatedness

a Pairwise comparison forewing shape

Species names	*Idea malabarica*	*Parantica aglea*	*Parantica nilgiriensis*	*Tirumala limniace*	*Tirumala septentrionis*
Papilio clytia ♀					
Papilio clytia ♂					
Pareronia ceylanica ♀					
Pareronia ceylanica ♂					
Pareronia hippia ♀					
Pareronia hippia ♂					

b Phylomorphospace forewing shape

PC2 (14.78%)

PC1 (81.45%)

1. *Parantica aglea*
2. *Parantica nilgiriensis*
3. *Tirumala limniace*
4. *Tirumala septentrionis*
5. *Idea malabarica*
6. *Pareronia hippia* ♀
7. *Pareronia hippia* ♂
8. *Pareronia ceylanica* ♀
9. *Pareronia ceylanica* ♂
10. *Papilio clytia* ♀
11. *Papilio clytia* ♂

a   Pairwise comparison forewing dorsal colour pattern

b   Phylomorphospace forewing colour pattern

1. *Parantica aglea*	6. *Pareronia hippia* ♀
2. *Parantica nilgiriensis*	7. *Pareronia hippia* ♂
3. *Tirumala limniace*	8. *Pareronia ceylanica* ♀
4. *Tirumala septentrionis*	9. *Pareronia ceylanica* ♂
5. *Idea malabarica*	10. *Papilio clytia* ♀
	11. *Papilio clytia* ♂

a Convergence

Convergence (C1)

Batesian mimics · Aposematics · Female-limited mimics · Monomorphic mimics

b Rate of trait evolution

Shape   Colour pattern

T. septentrionis
T. limniace
D. genutia
D. chrysippus
P. aglea
P. nilgiriensis
E. sylvester
E. core
I. malabarica
C. erymanthis
K. inachus
M. leda
P. hippia ♀
P. hippia ♂
P. ceylanica ♀
P. ceylanica ♂
H. glaucipee
L. nina
I. pyrene
A. albina
A. indra
C. aurora
C. danae
P. clytia ♀
P. clytia ♂
P. demoleus
T. aeacus
G. agamemnon
G. doson

Rate
5
4
3
2
1