

New evidence of feedback animated process in genetic evolution, an analysis of transient flow in the phyletic succession linking G. pleisotumida and G. tumida

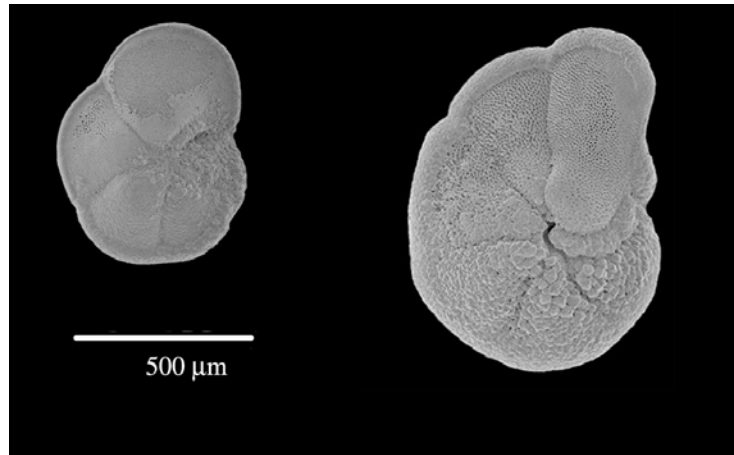
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1 *Abstract.* - The evolutionary transition from planktonic foraminifera G. pleisotumida to
 2 G. tumida provides an unusually detailed picture of a single speciation event. The
 3 transition is marked by a complex change in shape and an overall tripling in size of the
 4 organism over 2 Myr and directly appears to follow trends that accelerate and decelerate.
 5 Mathematical tests for internal symmetry of variation, for flowing shape in the
 6 succession of slopes and the physical mechanisms involved rule out random walk as an
 7 explanation. Both light and strong smoothing display the clear dynamic shapes
 8 common in feedback animated systems exhibiting fluctuation on multiple scales, typical
 9 of natural systems. A way to explain the presence of classic growth and climax phases
 10 of developmental processes bridging steady states seems required, even if still
 11 speculative for lack of any identifiable mechanism. Some of the requirements for such
 12 mechanisms are discussed, along with how ordinary emergent feedback animated
 13 systems seem necessary to explain the typical gaps between stable states, the punctuated
 14 equilibria, in the general fossil record. Some of the other possible causes for rapidly
 15 fluctuating and transitional flowing shapes in the trends of changing biological forms are
 16 also briefly discussed.

17 *Keywords:* planktonic foraminifera, G. tumida., pattern recognition, evolution,
 18 punctuated equilibrium, random walk, growth, complex systems, feedback animation



G. pleisotumida and *G. tumida*, electron micrographs taken by H.Hayashi (IGPS).

The shapes of things generally reflect their underlying structures, with a few notable exceptions. What appear to be trends in the fossil record might or might not reflect the underlying causes of genetic variation and selective pressures. Trends in evolution might also be considered to reflect nothing more than accumulating random variation, since that is frequently considered as a default hypothesis for the mechanisms of genetic change. Roopnarene (2003) reviews the literature on the subject finding that the study of rates of evolutionary change have generally not been fruitful, with little clear correlation between rates and behavior except that the longer the time span is considered the less behavior is apparent. The shorter period events in the fossil record are often assumed to be random walks, the accumulations of random steps that often visually appear to have rough shapes or directions like the changes seen in the fossil record, even though the underlying process of random accumulations of change has none. Whether random walks of biological characters actually occur is another question, however, is weakly supported except by assumption. Theoretically, characteristics of an organism that have no effect on survival could randomly wander,

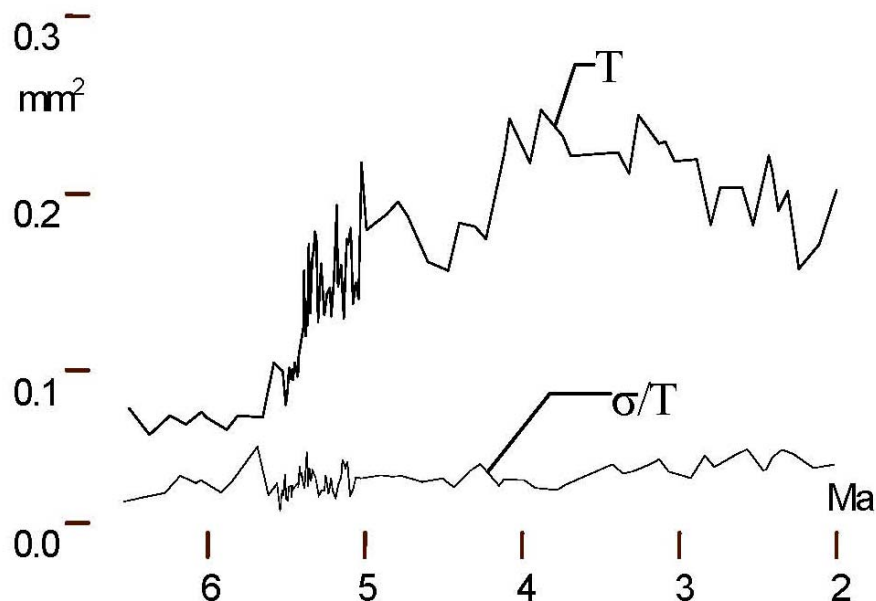
1 appearing to represent trends in evolution that actually aren't meaningful. The most
2 interesting 'rate events', though, are the gaps in the fossil record, the events that can not
3 be studied since there no data. Those of the shortest period, the common gaps in the
4 fossil record at speciation, imply rates of change that are infinite and were first described
5 as 'punctuated equilibrium' by Eldredge and Gould (1972) .

6 This study reexamines a classic example of evolutionary trends, the transition
7 between the plankton species Globorotalia pleisotumida and Globorotalia tumida
8 published by Bjorn Malmgren et all. (1983). The data shows an overall tripling in shell
9 size, following a variable transition of variable rapid change connecting relative starting
10 and ending steady states. Malmgren's data was later examined by Bookstein (1987),
11 and various others. As Bookstein saw it, the appearance of a succession of trends could
12 not be read as reflecting the punctuated gradualism claimed by Malmgren et all. (1983)
13 because an accumulative range test did not rule out the possibility the data could have
14 been produced by a random walk. This conclusion can now be reversed with good
15 confidence using more direct statistical tests for the properties of random walks and the
16 mathematical opposite of random walks, continuous flows, and also by considering the
17 physical mechanisms available.

18 MATERIALS AND METHODS

19 *Preliminary examination of the data.* - Globorotalia tumida is a predominantly warm
20 water planktonic foraminifera first identified by Brady in 1877. The data published by
21 Malmgren et al. (1983), (Figure 1), shows the average size of the shells (oriented
22 silhouette area) from 95 sediment samples spanning the last 7 million years, including
23 the transition from the G. pleisotumida to G. tumida beginning around 5.5 Ma. The
24 graphs show the first 86 of the 95 recorded data points to shorten the time axis and focus

1 the graphics on the period of interest. The samples of about 50 specimens each were
 2 gathered from a single 140 m Indian Ocean sediment core from site 214 of the Deep Sea
 3 Drilling Project. It provides a particularly high quality source for measures based on
 4 the fossil record, an all but perfectly continuous record of a single lineage over a long
 5 period from a single stable environment. The source is not prone to the worst normal
 6 defects of the fossil record, that fossilization is usually a rare and scattered occurrence,
 7 containing information strongly biased toward the present (Raup 1987). The dating of
 8 the layers of the core seems reasonably reliable as well, estimated by the magnetic
 9 guidepost method of Ness et al. (1980). The species appears to have been readily
 10 identifiable, abundant in every sample, to represent a single global species freely
 11 circulating in ocean currents and to display only lineal morphological succession
 12 without lineal branching (Malmgren et al. 1983). The drilling site is believed to have
 13 been geologically stable over the period.



1 Figure 1. Mean Profile Area of G. *tumida* fossils from B. Malmgren et al. (1983) DSDP
2 site 214. (T) The change in mean size of this common plankton over six million years
3 showing 86 of the recorded 95 samples¹ of about 50 specimens each. (σ/T) The ratio of
4 standard deviation within each sample divided by the mean.

5 Each of the samples consisted of approximately 50 micro-fossils taken from about
6 6-8 cc of mixed ocean sediment from 2-3 cm of the ~7 cm dia. core, representing
7 approximately 1000 year accumulations. Each sample was washed and filtered and the
8 specimens carefully picked at random by hand from the residue. The Samples were
9 taken at 10 to 30 cm (~20 Kyr) intervals at the Miocene/Pliocene boundary (the period
10 of rapid transition) and at about 2 m (~200 Kyr) intervals elsewhere. Measurements
11 were made of both specimen size and shape. Only the data on specimen size are
12 examined here though there was a similar trend in the measure of shape (Malmgren et al.
13 1983).

14 The trend in the data is readily visible, an appearance of a non-trending steady
15 state at beginning and end connected with a significant time period of transition with
16 progressively changing rates. The statistical analysis is complicated by the amount of
17 variation and by the variable rate of sampling, much more frequent during the period of
18 transition. The higher rate of sampling during the transition period was not repeated at
19 other times for statistical comparison, so it is not immediately clear whether the same
20 variability seen during the transition is present throughout. Still, sufficient numbers of
21 specimens were recorded in each sample for reasonable estimates of each sample's
22 standard deviation, and the ratio of standard deviation to the mean is fairly constant. On
23 average the sample standard deviation is 32% of the mean, quite large, and has itself a

1 standard deviation of 7%. The question is how to treat the data to determine whether
2 there are real shapes in the record and what those shapes might represent. The
3 analytical work for this study was done with a collection of lisp programs in AutoCAD
4 by Autodesk, the JMP statistical package by the SAS Institute and MS Excel. The
5 routines used for each are available on the internet as <http://www.synapse9.com/> as file
6 [names as Curve.zip](#), StepVar.zip and PaleoDoubleR1.xls respectively.

7
8 *Analytical methods.* - In order to qualify a time-series data set for trend analysis it is
9 necessary to first find it plausible that the data represents a continuous underlying
10 process and that its shapes of change would likely correspond to the underlying
11 mechanism of change. If it were statistically likely that the variation in the data was
12 produced by a random walk, and no other evidence is available to establish the
13 continuity of the underlying processes, it may not be worth speculating about the shapes
14 in the data as there is no demonstrated basis for that (Bookstein 1987). In the case of the
15 G.*tumida* transition, little is known about the underlying process of change and the
16 data's irregularity makes random walk seem at least initially plausible. A method
17 developed by Bookstein (1987) provides a range test to determine if a random walk
18 could produce the extrema of a given data set and the test fails to rule out random walk
19 when applied to the G. *tumida* data. A test for random walk developed by Gingerich
20 (1993) determines whether the distribution of step rates is within the limits expected for
21 a random walk. When applied in a test application, the method also failed to rule out
22 random walk for the G. *tumida* data. A review of these methods by Roopnarine et al
23 (1999) finds a high inherent likelihood of type II errors (incorrect failure to reject a null

1 hypothesis) indicating the low confidence that either test identifies random walks, but
2 simply fails to exclude them.

3 *Step variance test.* - A direct test for the presence of random walk concerns whether the
4 step variance in the data is accumulative or not (Henshaw 2000). The idea is to
5 measure whether the next change at any point is actually independent of prior steps
6 (indicating random walk) or tending in the opposite direction of prior steps (indicating
7 either complex fluctuation or symmetric noise about a norm).

8 The test is whether the variances of the steps in the data is the same for different
9 size steps (stable variation) or is larger for larger steps (accumulating variation). It
10 measures the degree to which successive changes in direction are locally symmetric and
11 cancel each other out. What it brings out is the clear statistical difference between an
12 accumulation of random changes and the natural behaviors with multiple scales of
13 fluctuation like many natural homeostatic systems. These are sequences that reflect
14 complex variation about either a fixed or variable norm. The analytical method uses a
15 version of the Hurst exponent (Mandelbrot 1969; Hastings and Sugihara 1993) and is
16 closely related to measures of fractal dimension in data.

17 The particular version of the Hurst exponent used here compares variances of the
18 step sizes rather than the mean of the step sizes which was chosen for having slightly
19 more consistent results. The sub-sequences for the test are created by skipping fixed
20 numbers of points in the data. If the sampling rate is k (the distance between points in
21 the subset), and v is the step variance (variance of their sequential differences), the step
22 variances for random walk data will increase at an average rate of $k*v$, showing the
23 effect of having accumulative variance. If the step variances do not increase with

1 increasing k , the statistically abnormal shapes in the data were not produced by
 2 accumulative variation. It indicates that noise suppression can then be used to
 3 potentially reveal meaningful shapes.

4 A theoretical random walk is a sum of independent copies of a random variable
 5 with variance v . The larger the steps through the sequence, the larger the variance
 6 (since it's additive). As such, a sub-sampling of a random walk is also a random walk,
 7 but with a variance of $k*v$. In contrast, a sequence with variation about a constant norm
 8 will tend to have the same absolute step variance at whatever rate it is sampled, a
 9 constant. This relation is displayed in the slope of a log/log plot comparing step sizes
 10 and variances, giving the Hurst exponent (H_σ) as the slope:

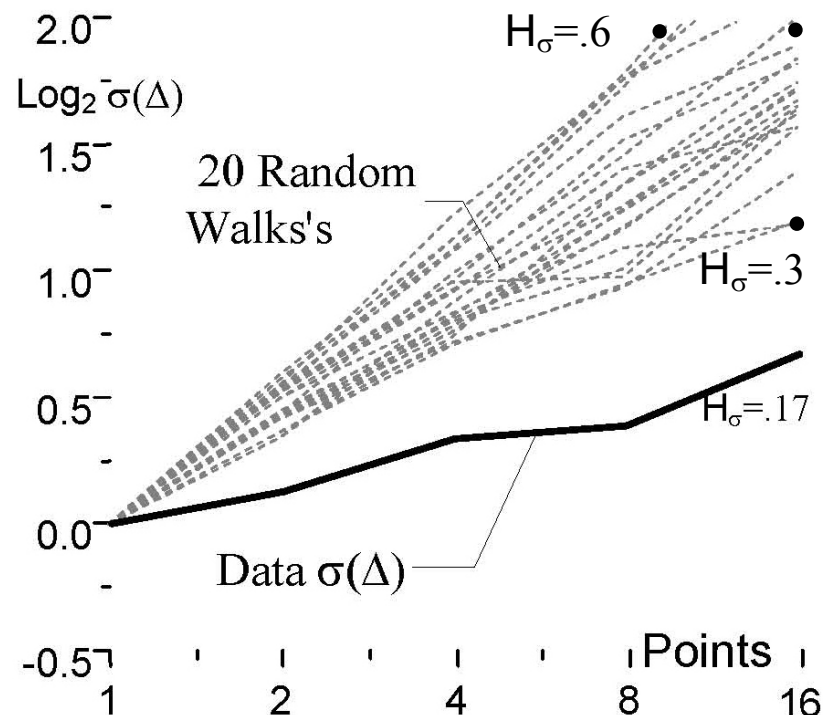
$$11 \quad H_\sigma \cdot \ln \frac{k}{j} = \ln \frac{v(S_k)}{v(S_j)} \quad (1)$$

12 where j and k are the number of points, or time periods, for re-sampling used to make
 13 sub-sequences S_j and S_k , with $v(S_j)$ and $v(S_k)$ their step variances. For a random walk
 14 $H_\sigma = 1 \pm \epsilon$ where ϵ is the tolerance allowed in any given case for not having an infinite
 15 number of points. For a sequence with only normal random variation $H_\sigma = 0 \pm \epsilon$.

16 By numerical experiment with 20 random walks (see Figure 2) the spread that
 17 occurs is a rough measure of the 95% confidence interval for the range of random walks,
 18 and displays the close clustering of random walks under this test. Sequences with H_σ
 19 well outside this interval (values of H_σ well outside .33 and .65) can be confidently
 20 distinguished from random walks and probably represent some regular continuous
 21 process combined with noise. The test can be somewhat loose for ruling out a

1 presumption of random walk, since the object is only to find a reasonable doubt that the
 2 shapes are purely a product of noise. A strong indication that the data is not a random
 3 walk then just adds interest, still leaving the validation of any shape analysis to whether
 4 its implications are well supported otherwise.

5 If a random walk can be ruled out, and not just brought into question, it just
 6 increases the presumption that the shapes in the curve represent corresponding physical
 7 processes which can be validly explored by noise and shape suppression using iterative
 8 methods like Gaussian smoothing, or shape reconstruction by estimating missing
 9 derivatives (Henshaw 2000). To validate any results it remains, of course, to account
 10 for the sources of noise and correlate the suggested behavior with theory and
 11 independent evidence.



12
 13 Figure 2. Step variance test for G. *tumida* size, and 20 random walks, showing the trend
 14 of std deviations $\sigma(\Delta)$ for the differences between 2,4,8, & 16 point steps in the data.

1 The $H\sigma=.17$ value is the slope for G. *tumida*, showing a substantial departure from the
2 norm of random walks.

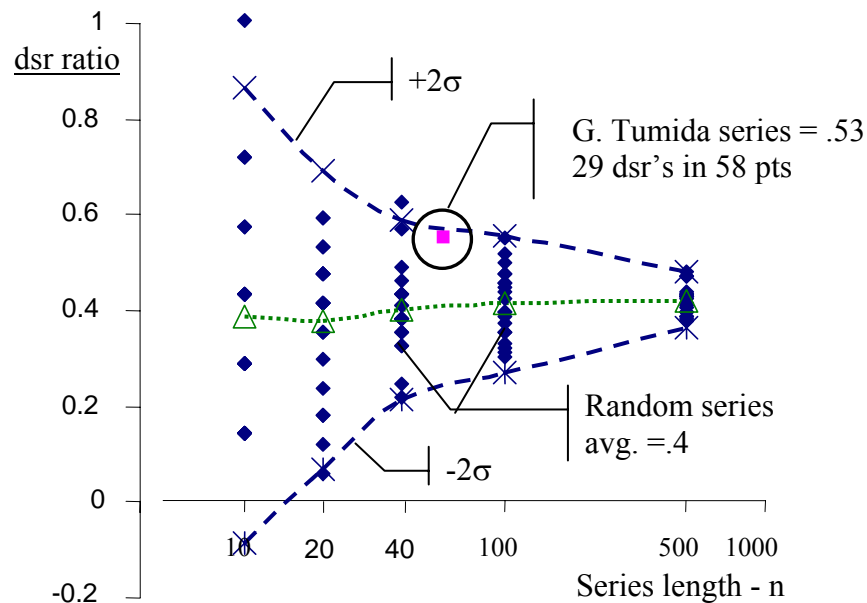
3 Apart from the helpful evidence of the statistical test it is also apparent that there is
4 a logical problem with postulating random walk of a whole population. If random
5 walk in the characters of the whole population occurs, it must be the result of some
6 pattern of change in the characters of individual organisms. Individuals within a
7 population can not continually make matching 'random' neutral changes at the same
8 time, and that is the only way the variation of individuals can produce a collective
9 random walk. It appears that for populations there may be no functional basis for
10 random walk. If the characters of individual lineages of a population exhibit
11 independent (rather than matching) random walks, the resultant mean value for the
12 population will be constant, with the variance within any sample continually increasing.
13 Assuming one approaches analysis moving from general to specific, the issue would
14 become one of the preferred order of considering statistical or physical possibilities,
15 rather than one of natural behavior. Since random walks of individual traits would not
16 produce random walks of population traits it would appear the 'null hypothesis' only
17 states a preference to qualify ones later analysis based on the data alone before
18 considering the feasible physical behavior of the system. The attempt to assure that
19 statistical analysis will be purely value-free, using the posture of 'naïve realism' that all
20 you have is your data with no knowledge of any connection between the points, that
21 they're just dots on a page, overstates the true case. In data there are lots of interesting
22 and confusing effects, of course. That would include the interesting cases where
23 random walks of neutral traits in individual lineages may occur, and could lead to


1 accumulative changes that have large affects combined with other factors in later
2 generations.

3 *Flowing shape test.* – Once it is clear that random walk would not explain irregular
4 population data one can try to find out how much of the variation is due to sampling the
5 inherent diversity in a population (noise), and how much is due to sampling complex
6 fluctuations in the population's processes of change. Flow is the property of some
7 physical systems that allows them to be approximated by mathematical functions.
8 Having flowing shape is the physical system corollary to the mathematical property of
9 the derivative, and a large part of what makes mathematics useful for describing nature.
10 In both cases it means that the succession of changes will have no kinks or breaks, and
11 so that the slope at a point when approached from either direction is the same. A
12 simple test of a time series data set to see if the underlying system is likely to represent a
13 process having continuous flows is to measure the number of sequences of three slopes
14 that have sequentially opposite signs, the number of double slope reversals or zig zag's.
15 It's surprising, but no mention of flow as a property of physical systems and the
16 statistical indicators that might demonstrate its presence in time series data were found
17 in several good statistical research handbooks (Hamilton 1994, Rice 1995 among them)
18 and a web search. From experience it appears that the question does not come up
19 because the continuity of natural processes is assumed to be mathematical, and their
20 physical continuity a function of the equation to be used in describing them and not a
21 physical property of the natural system.

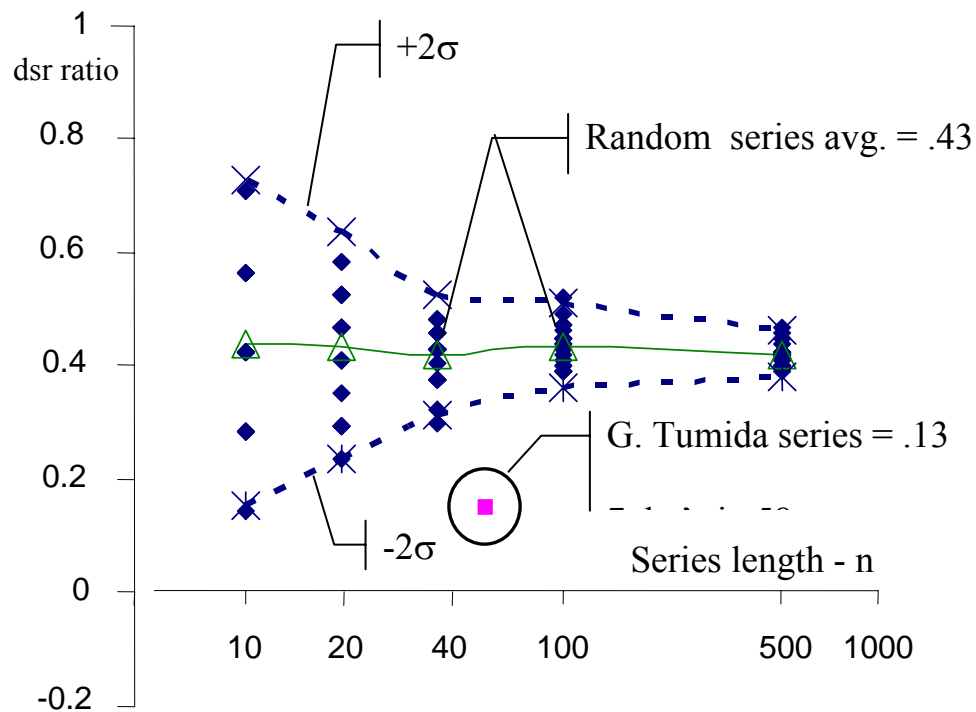
22 The direct measure for flowing shape use here is to count how often the slope
23 between points reverses twice in a row. In a curve with pure flowing shape and dense


1 enough points to describe it, there will be none. In curves with only random
 2 fluctuation there will be on average nearly half the possible number of double reversals
 3 possible. In particular, light smoothing does not reduce the number of double reversals
 4 for curves with shapes produced by random fluctuation (compare figure 3a & figure 3b).
 5 Sometimes light smoothing will greatly reduce the number of double reversals,
 6 producing a curve with a much greater degree of flowing shape. The likelihood, then, is
 7 that the data recorded a continuous but fluctuating process as is common for natural
 8 systems, which will show clearly when the noise in the data is gently suppressed.



10 Figure 3a. Fraction of double slope reversals (dsr) [] for 20 random series of
 11 varying length (10, 20, 40 & 100 points), w/curves for mean and 2 std. deviations above

1 and below, with value of .51 for the 58 point G. tumida data.



2
3 Figure 3b. Fraction of double slope reversals (dsr) [] for lightly smoothed
4 random series w/ mean & 2 std. dev. curves, and value for 58 pt G. tumida data.
5 Smoothing is by a 3 point center weighted kernel (1,2,1). Shows that light smoothing
6 does not change the mean frequency of slope inconsistency for noisy data, and
7 conversely that the irregularity of the G. tumida data originates from complex
8 fluctuation of larger period than the data in an underlying process with a flowing shape.

9
10 *Noise suppression.* - There is a noise component present in any sequence of measures.
11 A running average or centre weighted average of points trades a loss of shape for a
12 distribution of the noise making the underlying shapes more visible. A smoothing

1 'kernel' is the mathematical rule to be applied sequentially to clusters of points for the
 2 purpose. It's usually a simple distribution of 'weights' with a sum of one, such as:

$$3 \quad \text{for } -a < n < a \quad k(n) = \frac{e^{-|n|/2}}{\sum_n e^{-|n|/2}} \quad (2)$$

4 giving a Gaussian (bell curve) distribution of weights to a group of $2a+1$ points, used to
 5 calculate contributions from neighboring points in smoothing a sequence. Smoothing
 6 suppresses all variation in a sequence while giving previously invisible turning points in
 7 the data clear definition, making the series approximately differentiable.

8 *Scale space analysis.* - With repeated smoothing of a curve the smaller scale turning
 9 points are successively suppressed leaving only the principle turning points of the data.
 10 In most data sets there are several distinct scales of variation present, representing
 11 several scales of underlying processes (like ripples on waves on swells, etc.). A chart
 12 (see Figure 6) tracing the migration and disappearance of inflection points provides
 13 traceable shape landmarks for different scales of noise and different types of underlying
 14 behaviour present. These landmarks can serve as a fingerprint for making matches
 15 between different shapes and for identifying different scales of underlying behavior.
 16 The fact that all shapes can be deconstructed and compared in this way is now
 17 commonly exploited in computer vision (Lindberg 1994).

18 *Interpreting results.* - For most classes of behaviors there is a kind of taxonomy of
 19 familiar dynamical shapes associated with familiar behavioral processes. One of the
 20 available general taxonomies of shape is provided by the common forms of equations,
 21 distinguished by relationships of their derivatives (representing the classic types of
 22 physical systems). For example, the difference between a simple polynomial (having

1 only one, two or three exponents for example, and thus higher derivatives flattening to
2 0) and an exponential (infinite series of exponents and all higher derivatives present and
3 of the same sign) may be clearly visible in the shapes in a curve. Those revealing
4 shapes may be enhanced at one scale of smoothing of the data or its step differences and
5 not at others (the curves of the 'step differences' in sequential data display the slopes of
6 the data similar to the way derivatives display the slopes of functions). One may also
7 use specialized techniques to avoid the shape distortion of Gaussian smoothing such as
8 derivative reconstruction (Henshaw 2000).

9 For each recognizable mathematical shape there are a set of possible
10 corresponding behavioural processes. It is the goal of curve interpretation to identify
11 them. For example, it is a primary interest to distinguish between the shapes of
12 transient developmental processes (endogenous or self-organizing system events) and
13 the effects of some secondary processes (exogenous effects). An 'S' curve, for example,
14 could equally represent a diffusion of effects from some remote cause or evidence of a
15 local self-organizing cascade directly involving the measured quantity. This difference
16 often can not be determined from examining the data alone, and sometimes a full
17 examination of many plausible mechanisms and correlation with other data is required to
18 determine whether the apparent shapes in a curve do in fact correspond to plausible
19 underlying processes.

20 RESULTS

21 *Direct inspection.* - The upper curve on Figure 1 shows the mean of each of 58 samples.
22 The lower curve the ratio of the standard deviation of each sample to its mean. If the
23 individual lineages represented were each varying as a random walk the variance of the

1 population would increase linearly over time, whether there were trends in the average
2 or not, but that is clearly not the case. One of the other interesting issues is that the
3 organism may be reproducing as a clone, as plankton of this type sometimes do, and the
4 models of evolution depending on genetic mixing through sex or other mechanism might
5 not apply. If that were the case every lineage would vary independently, however,
6 so you would also expect a substantial increase in population variance over time for
7 many reasons. That is clearly not happening. If anything, the population variance
8 declines a little in the period of most rapid change. The one wild scenario that could
9 disguise independent random variation of each lineage as a separate species is if only
10 one lineage survived over and over, as all others died out, so that all individuals
11 remained descended from the same ancestor a fixed number of generations before.
12 Barring that unlikely scenario the measure of size seems to be a corollary measure of
13 non-neutral genetic change and the different lines seem to share genetic material by
14 some means.

15 *Step variance test.* - Though it does not seem reasonable that a whole population could
16 perform a random walk, with all lineages making the same accumulating neutral
17 changes, it's the required presumption under a widely accepted null hypothesis
18 (Bookstein 1987). To use the step variance test, various sub-series of the 95 data
19 points (Malmgren et al. 1983) were prepared consisting of every 2nd, 4th, 8th and 16th
20 points, and the variances of each these new series plotted. These are graphed in Figure
21 2, along with the same measures for a group of 20 random walks of 95 points for
22 comparison. The difference is visible. The value of the slope ($H\sigma$) for the G. *tumida*
23 data is .17, a fraction of the mean for random walks of 1.0 and well outside the range of
24 two standard deviations from the mean for random walks, by graphic estimate, between

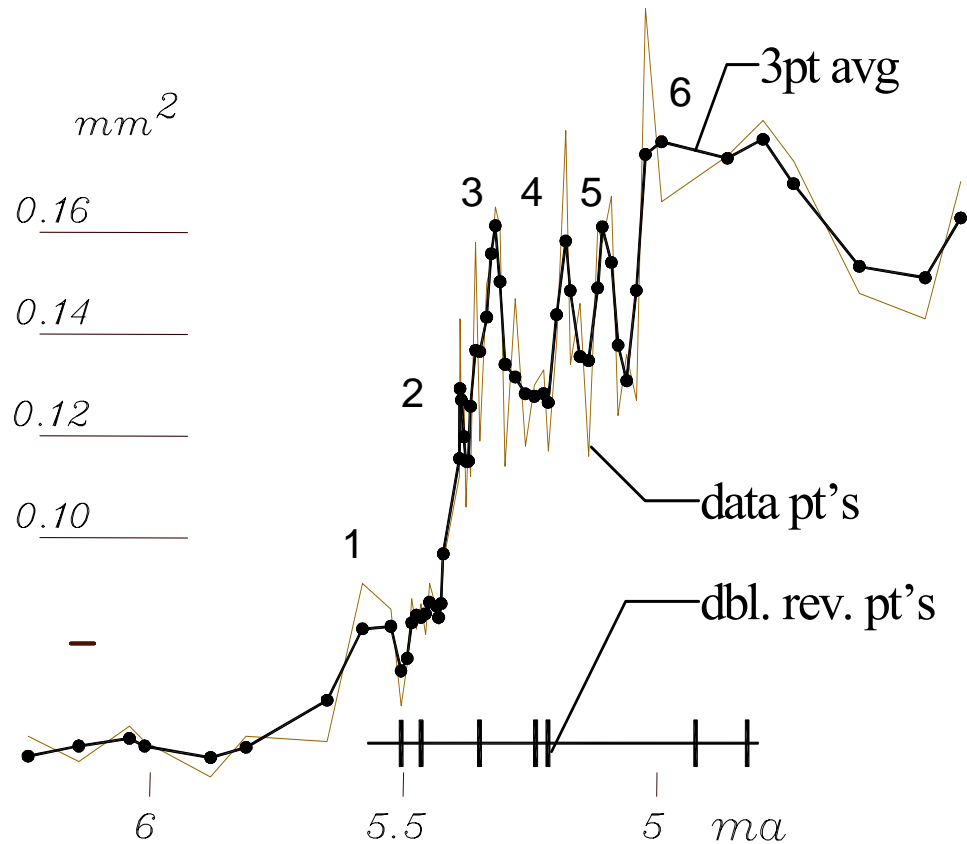
1 .47 and 1.53. This indicates that the structure of the variance is locally symmetric and
2 that the G. *tumida* data is not an accumulation of random variation, with a better than .05
3 level of confidence.

4 *Trend analysis.* - Having determined that the random noise in the series is largely
5 symmetric, the G. *tumida* data was then treated as possibly representing a continuous
6 process superimposed with fluctuation and noise. Figure 4 shows a close up view of the
7 rapid transition section of the data, with very light smoothing, a 3 point centre weighed
8 average. There are only 5 double reversals in the gentle smoothing of this sub-sequence
9 of 58 points, demonstrating a high degree of slope continuity. A sophisticated
10 mathematical test for derivative continuity in a data set is what is needed, but unknown,
11 even if clearly visible in the flowing shape, visually demonstrating what the step
12 variance test demonstrated was likely.

13 The step variance test showed that the data varied about a moving norm, and the
14 slope continuity after light smoothing shows both how closely the data follows that
15 norm, and that the norm tends to change direction with flowing shape composed of
16 progressions of small steps as in derivative continuity for mathematical functions.

17 The prominent fluctuations labeled 1, 2, 3, 4, 5 & 6 would be easily dismissible as
18 noise, were it not for the fact that they are each traced by curves with progressively
19 changing slope, not randomly changing slopes. These fine scale fluctuations have
20 durations of about 150, 25, 140, 80, 80 and 600 thousand years, respectively. The way I
21 measured the duration was between the midpoints of fluctuation pairs in the moving
22 average. Fluctuation number 6 is treated as the long regular wave shown, though the

- 1 longer sampling rate at that time might well disguise rapid flowing fluctuation of the
- 2 type seen in the earlier periods.



- 3
- 4 Figure 4. Enlarged view of the G *tumida* transition with a 3 point centre weighted
- 5 moving average. In 58 points the smoothed curve has only 7 consecutive reversals
- 6 indicating a high degree of slope continuity.

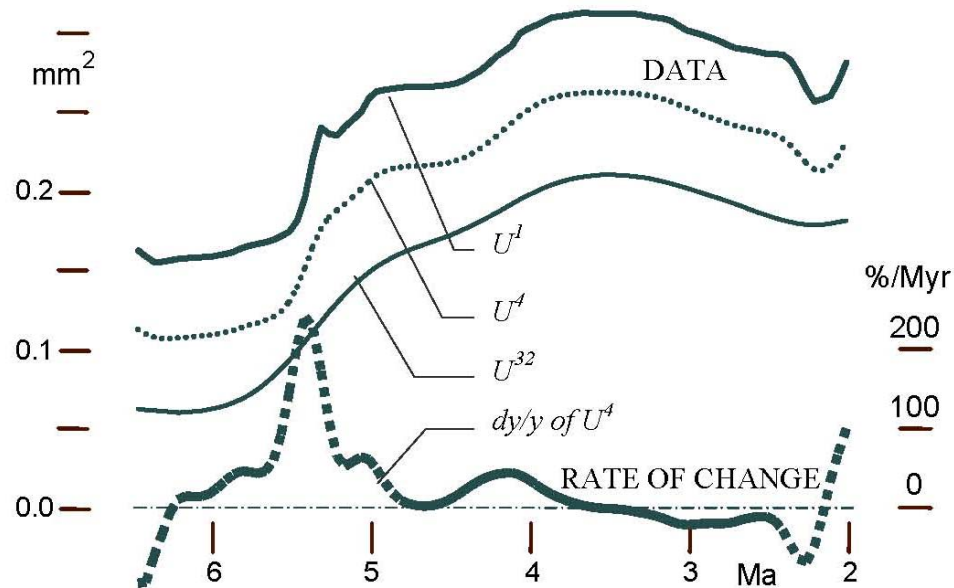
- 7 It is typical of continuous systems to have fluctuations of large and small scale
- 8 superimposed so that the underlying trends, and long duration fluctuations are easily
- 9 recognized only after suppressing the smaller ones. That is particularly true for looking
- 10 at a trace of the point to point slopes of a sequence, the first differences. They tend to
- 11 look highly erratic if the smaller scale fluctuations are not eliminated first. When the

1 smaller scale fluctuations are suppressed enough, progressive rates of changing slope
2 show the dynamics of the underlying system. It's a matter of glossing over the ripples
3 so you can see the waves. The 'ripples' in this case, the several short lived peaks, are
4 apparently real individual events, but superimposed as fluctuations on a larger event.

5 One major hazard of this approach to interpreting data is that any sequence of
6 measures might reasonably represent overlapping information from several different
7 behavioral systems happening at the same time. In this case, because the species was
8 easily identified and branching was not apparent (Malmgren 1983) and the variance has
9 no evident trends, it appears the measure is a consistent indicator of only one thing. A
10 more thorough examination of the individual specimen data might help prove the case in
11 either direction, though. That said, the further display of the character of variation in
12 the sequence assumes that there is one process with various scales of fluctuation and
13 stripping them away will expose a central behavior. Successive shape suppression
14 reveals a simple shape with a recognizable derivative, and is followed by scale space
15 analysis to display the different levels of irregularity in the scales of the shape.

16 Figure 5 shows an initial strong Gaussian smoothing (top curve), further
17 smoothing after 4 and then 32 more repetitions (middle two curves), and the derivative
18 of the middle smoothing curve (bottom). The curve scales are shifted so the curves can
19 be seen separately. The top curve in Figure 5 was produced using a Gaussian
20 smoothing kernel with a 17 data point spread (Henshaw 2000). The degree of initial
21 smoothing was arrived at experimentally, intended to represent the least suppressed
22 good representation of the overall shape. The point spacing of the data was then
23 regularized at .05 Myr, by periodic integration, (converting to a sequence with equally

- 1 spaced points). This is required so repeated smoothing will have a uniform effect.
- 2 Then the further smoothing was done with a 9 point (.4 Myr) Gaussian kernel, first with
- 3 4 iterations (U4) and then 32 iterations (U32).



- 4
- 5 Figure 5. Revealing the behavioral shape with Gaussian smoothing. Three levels of
- 6 smoothing U1, U4, U32 (each offset by .05 on the mm2 scale for visual separation) and
- 7 the first log derivative of U4. U1 is a 17point running average of the raw data for noise
- 8 suppression. After 0.05 Myr data point spacing equalization, repeated smoothing is
- 9 performed with a 9 point (.4 Myr) Gaussian kernel.

- 10 One secondary technical issue concerns the order of these steps. The initial
- 11 smoothing kernel used a set number of points from the original data set (rather than a set
- 12 time interval) to define the range for the initial smoothing. After that the point spacing
- 13 was changed using the interpolated values of the initial smoothing curve at regular time
- 14 intervals. The reason is partly that Gaussian smoothing produces distorted results when

1 the point spacing is not constant. Another is that the initial smoothing is for the purpose
2 of noise and fluctuation suppression, and noise and fluctuation in data is on the scale of
3 the actual point spacing, whether regular or not. Once the initial smoothing is done
4 further smoothing is not for noise suppression, but shape suppression, to make the rate
5 of change curves more readable and to suppress inflection points to see which are the
6 most robust. Experiments were also done with regularizing the point spacing first and
7 found to produce greater distortion of the more detailed portions of the curve.

8 Whether the smoothing was ultimately useful depends on whether the underlying
9 shape is recognizable and can be associated with some particular underlying mechanism.
10 Getting to that determination is the reason for allowing an initially weak hypothesis, to
11 try looking for something hoping to confirm the details later. Another note is that any
12 curve trend analysis that uses a symmetric spreads of points to smooth data will develop
13 meaningless shape artefacts near the beginning and end because of the asymmetry of the
14 end conditions. This is evident in odd tails seen in all the smoothing curves of Figure 5,
15 especially pronounced in the derivative. One could hide this by doing smoothing on a
16 longer data set and cutting off the ends, but data is scarce and it's valuable to be
17 reminded of the effect of one's own tools so I just leave them as they come. In this case
18 the normal smoothing kernel had a .2 Myr spread on each side of any point. To adjust,
19 at that distance from the end of the curve the smoothing kernel starts losing points and
20 at the very end is reduced to 1 point so as the shape of the rest of the curve is suppressed
21 the end point never moves.

22 To identify the underlying physical processes from a curve shape one can compare
23 a curve based on one kind of measure with others, perhaps to see if their turning points

1 line up, for example, or use curve fitting with a model equation to investigate the
2 possibility that the underlying system has a consistent mathematical structure.
3 Sometimes derivative progressions can be directly identified by their shape. Here, one
4 may recognize in the derivative (Figure 5, dy/y of U4) the classic shape of an isolated
5 positive rate spike bounded by relative steady states, identifying it as some dynamic
6 event that starts and stops. It directly suggests the progressively increasing and then
7 decreasing positive rates of change of a growth system change of state. The singular
8 spike in the derivative is reinforced by the progressive slopes evident both in the
9 smoothing curves and seen through the noise and smaller scale fluctuations in the
10 original data (figure 1) and the light smoothing (Figure 4). In most cases these would
11 be clear indicators of a dynamic change in an internally organized complex local system
12 guided by positive and negative feedbacks. What those might be in this case and
13 whether it is reasonable to consider that possibility for speciation events, of course,
14 remains entirely open.

15 *Scale Space Display.* - Figure 6 is a map of the movement and suppression of the
16 inflection (curvature reversal) points resulting from extended repetitions of Gaussian
17 smoothing. Each bump on the curve is represented by a pair of inflection points, one on
18 either side. These serve as landmarks in the curve shape. As a bump is slowly
19 smoothed out with higher repetitions of smoothing the scale space chart will show two
20 lines from the bottom of the chart coming together and joining at the point where the
21 bump on the curve vanishes. The diagram demonstrates the endurance of each
22 inflection point (whether representing some source of noise or some kind of behavioural
23 fluctuation). The curves shown were drawn by plotting the location of each inflection
24 point for each smoothing level and then manually fitting a b-spline curve to pass through

those points to show the implied continuous path. More sophisticated methods are available (Lindberg 1994, Mokhtarian and Mackworth 1992). The apparent shape scale boundaries at approximately U1.5, U4.5, U64, and U1024 identify groups of successively more robust inflection points. Inflection point A remains through 512+ iterations of smoothing.

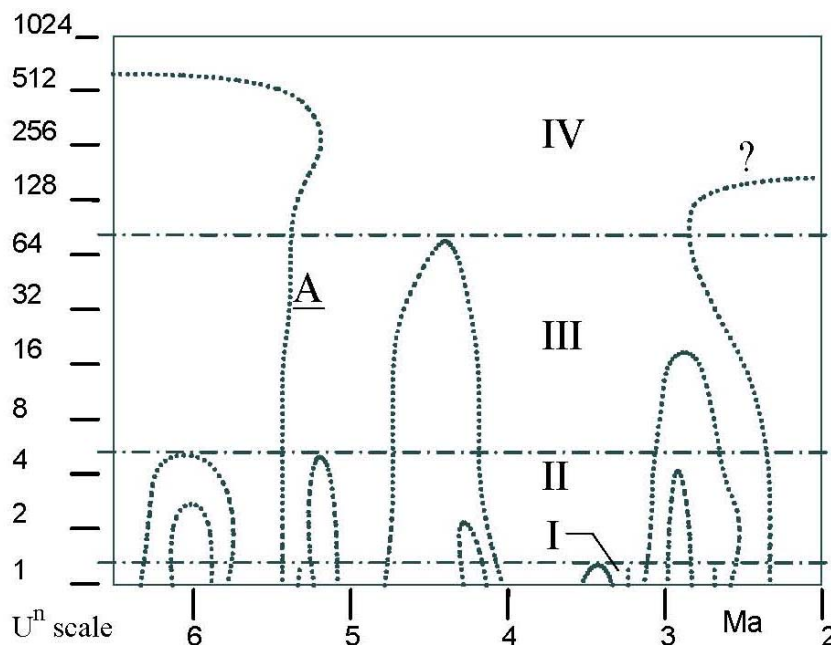


Figure 6. Scale space diagram. Tracing the location of inflection points through 1024 iterations of 9 point (0.4 Myr) Gaussian smoothing. General shape scale levels I, II, III, IV representing four general scales of inflection point persistence with line A coinciding with the prominence in the derivative curve in Figure 5.

Based on the visual indication of fine grain behaviour (Figure 4) the first shape scale regions (I & II) where 5 pairs of fairly robust inflection point traces drop out represent a consistent level of fluctuation in the underlying process. Perhaps with if started with a lighter smoothing the shape scale analysis would be able to separate what

1 is apparently a very low level of actual noise in the data from the strong fine scale
2 fluctuation. Whether that level of fluctuation represents variation in a central process
3 or transient side processes is not clear. It is also not clear whether these fluctuations are
4 endogenous or exogenous in origin. The do look enough alike as if they are related
5 though.

6 The two pairs of inflection points that drop out in period III are of a different scale
7 and probably reflect some different cause than those of smaller scale. Any growth
8 system will trigger both rapidly and slowly changing environmental responses and in
9 looking to associate causes with affects one would look for processes with matching
10 response times.

11 The last inflection point to the right, starting from about 2.3 ma at U1 appears to
12 be a false positive. If you look carefully at the data shape at 2.3 Ma (Figure 1), for
13 example, you'll see a large fluctuation largely the result of one exceptional point at the
14 very end of the sequence where the data. That leaves an artefact in the smoothing
15 curves because the smoothing kernels run out of points to interpolate at the end. As
16 usual, the smoothing kernel leaves the end point unchanged, reducing the point range of
17 the kernel from the normal 9 to 7 to 5 to 3 to 0 points, so that shape suppression declines
18 at the ends. As a result, the retention of shapes near the ends is less significant.

19 DISCUSSION

20 What Malmgren (1983) first found in this same data he called 'punctuated
21 gradualism', because it appeared to display a period of increased random variation and
22 directed selection. It was then interpreted as a random walk (Bookstein 1987),
23 indicating a complete absence of underlying rates or processes based on a failure to rule

1 out the null hypothesis, and the matter was treated as closed. What the curve shape now
2 visible shows is different and the question has to be revisited whether it has anything to
3 do with evolution at all, and what that could mean.

4 Changes in the profile area of a plankton species could conceivably be due to a
5 simple matter such as a change in ocean temperature, or shifts in nutrient currents
6 (ecophenotypic change). It could also result from ecosystem change, where a
7 community of species develops a mutual support and reliance, such as a species taking
8 on a symbiotic partner (ecosystem evolution without species evolution). These and
9 other mechanisms could potentially produce significant changes in phenotypes by
10 themselves, or together with several factors having enhanced combined effects. There's
11 no necessity to conclude from the shapes of the curve that the dynamic event visible
12 here originated from genetic evolution.

13 The response of plankton to ocean temperature without genetic change is well
14 known and even commonly used as a measure of ocean temperature (Smolka 1991,
15 Schmidt et. all. 2004, 2005). Smolka (1991) reported summer and winter temperatures
16 from measurements taken from the same sediment core (DSDP 214) that the G. *tumida*
17 samples were taken from. His samples were taken about a ½ Myr apart and, except for
18 a $4.0 \pm 0.3^\circ \text{C}$ dip and recovery in summer temperature in the 1 Myr before the G. *tumida*
19 transition, show fairly constant summer and winter temperatures during the period.
20 Schmidt et. all. (2004, 2005) provide a comprehensive global survey of ocean
21 temperatures and plankton size relationships, including a review of the G. *tumida*
22 transition data. The combined data show a clear and fairly steady global increase in
23 plankton size of about 25% over the past 10 million years. Schmidt & Kucera (2005)

1 recently updated this assessment with the observation that the general size increase trend
2 observed was not actually unidirectional, but also perhaps responsive to macro-ecologic
3 events, though none of those listed appear to coincide with either the timing or degree of
4 the 5.5ma transition of G. tumida. The different drawing scales used by Schmidt et al.
5 (2004) give the G. tumida transition the appearance of having a similar slope to the
6 general trend. The actual average rate of change during the G. tumida transition is
7 200% in ½ Myr, about 160 times as fast as the global average plankton size trend,
8 however. The steepest sustained rate of change for G. tumida, 12 data points over 110
9 kyr, was 550 times as fast. That reads as a difference in kind, not just in degree and is
10 inconsistent with the general temperature influence demonstrated.

11 No hard evidence was found of other environmental or ecological changes, though
12 it would seem unlikely that any one global species would change dramatically without
13 other things changing at the same time. One expert on the subject, Richard Norris
14 (1996) has reported that G. tumida has never hosted a symbiot organism, though that is
15 fairly common in similar plankton species and when it occurs it does tend to increase the
16 species size. He also confirmed that a similar transition is visible in Atlantic Ocean G.
17 tumida lineage samples, though reportedly, the little G. pleisotumida appear to linger
18 somewhat longer.

19 *Punctuated Equilibrium*. - In summarizing the debate over punctuated equilibrium
20 begun by Eldredge & Gould (1977), Prothero (1992) provides 15 citations including
21 Gould (1992) and Stanley (1992) for what still seems to be the consensus, that gradual
22 random genetic drift prevails for microscopic protestants including foraminifera like G.
23 tumida. The G. tumida transition does not fit that description though, and may well be

1 unique or rare. On the surface, though, the unusual G. *tumida* transition pattern could
2 be taken to neatly fit the shape of the fossil record gaps that give rise to the punctuated
3 equilibrium puzzle. It shows a definite transition between distinct stable species in a
4 relatively short time by a continuous incremental process. This would seem to be a
5 testable hypothesis perhaps, except that the gaps needing explanation arise directly from
6 a distinct lack of data in the fossil record. A direct test using this approach requires a
7 fairly large number of samples. This analytical approach does draw out a wealth of new
8 kinds of information from unspectacular data, however, so revisiting old data may be
9 productive, and tell another story than has been assumed as the G. *tumida* data does.
10 Testing sequential data for the presence of behavioural fluctuation hidden in minor
11 noise, rather than assuming that irregularity is entirely noise or random walk, would
12 probably turn up a great deal more clear behavior.

13 The central problem of punctuated equilibrium (Gould & Eldridge 1972) is that the
14 more complex species tend to appear abruptly in the fossil record and remain unchanged
15 for long periods, implying that speciation occurs relatively rapidly, in relatively small
16 and localized populations, and produces relatively stable new organisms that don't
17 continually change with shifting environmental pressures. After twenty years of
18 research and debate a consensus agreement was generally reached (Prothero 1992)
19 which remains commonly reaffirmed (Geary 2003), based largely on the abrupt
20 appearance of species in the fossil record, their usual structural stability and a complete
21 lack of evidence for how they are created for lack of evidence.

22 The data collection problem for the higher species is that the fossil record may
23 provide an example of one out of a few thousand generations and speciation may occur

1 in a few hundred. Given that sampling pattern there would be no way to trace the shape
2 of how it happens no matter how or where it occurs. The direct approach to answering
3 the question might be closed, but there may be others. There are various modern
4 collections of fauna and flora in the drawers of century old naturalist collections for
5 various locales that might accidentally capture a sequence of generations displaying the
6 necessary pattern kind of change. How frequently that would be found is hard to
7 estimate, but transient flowing shapes in characters may never been looked for before
8 and if one were looking with the right analysis tools, it seems likely one would come
9 across more examples.

10 *Potential modes of feedback.* - One logical way for larger jumps of genetic change to
11 occur in evolution is for an accumulated random walk of neutral genetic changes to later
12 be found to aid or hinder reproduction. That might occur by itself, or in combination
13 with and amplify some other genetic or ecological change, Prothero (2000). That
14 mechanism could produce a sudden multiplication of population numbers for one
15 lineage, but not a progressive or coordinated pattern of mutations for a whole
16 population. What's needed to fit the pattern of large complex change in short periods of
17 time is for structural stasis to give way to rapid change and then go back to stasis again,
18 by a sequence of small steps. That very precisely calls for feedback.

19 One plausible genetic mechanism that could do that, would be for the success of
20 one mutation to increase the frequency of other mutations of similar kinds. That way
21 the new variations would serve to 'explore' the region of positive phase space of the
22 original. One might think of it as suggested by the fact that the growth of an organism
23 is itself a branching tree of events and that evolution is a stepwise modification of that

1 tree's branches. I know of no particular branching structure in the genome, but
2 something having that effect is implied for opportunistic genetic progressions to occur.
3 It requires some kind of genetic structure that allows an expansion and then contraction
4 of possible changes, and that pattern should leave some kind of statistical evidence. A
5 clever analysis of the data for individual specimens from the G. *tumida* lineage might
6 possibly show the cloud of variation around any given mean to be biased in the
7 directions of future progressive change, for example. Another avenue for finding
8 evidence of genetic variation sensitive to feedback would be to look for variation
9 clustering that changes over time in the background variation for any species.

10 One pattern of evolution that might be explained by a branching/feedback mode of
11 evolution is the quite common tight fit between special traits of different species. It
12 suggests that a genetically localized coevolution occurs, i.e. restricted to a limited cluster
13 of features. Evolution by distributed variation throughout the genomes of interacting
14 species would be more likely to develop a diversity of relationships instead. A
15 branching variation would potentially allow two species to travel a very narrow channel
16 of mutual reinforcement leading to a complexly coordinated narrow change.

17 One potential biological mechanism for producing a branching genetic structure
18 and variation sensitive to feedback is suggested by the patterns of proportional
19 relationships in the shapes of organisms first carefully documented by D'Arcy
20 Thompson (1917 & 1942). That work was not rigorous in every way, but is a work of
21 enduring popularity focusing on an aspect of body form, proportional geometry and
22 comfortable fit, nearly everyone recognizes. It apparently addresses something real that
23 is not yet well explained.

1 A similarly clear appearance in evolutionary change is that changes tend to
2 involve the migration of the endpoints, rather than the starting points, of biological
3 growth. Because evolution involves more change in the characters that develop late in
4 individual organism growth the appearance is that change occurs more at the ends of the
5 branching process of development. A second appearance is that the growth of
6 organisms does not end by internal exhaustion or conflict, suggests there must be some
7 coordination of the stopping points for development's branching process. The limits of
8 growth for organisms never seem to be starvation or organ congestion and the taught
9 stretching of skin, so the various branches of development in growth must turn
10 themselves off from the inside.

11 The question here is less how growth is turned off from within and more whether
12 the alteration of a set point for the end of growth for one thing might affect the endpoint
13 of others. If there is some kind of interrelated proportional system for the set points for
14 an organism's growth climaxes, a physical structure corresponding to the
15 proportionalities we observe, change in one might have various kinds of ripple effects.
16 One popular image of such ripple effects of small changes in complex systems is the
17 idea of 'chaos'. Complex balances can begin to wobble or meander when slightly
18 perturbed, until a new balance is found. Given environmental rewards and penalties
19 some of these would be reinforced by enhanced reproduction and some constrained by
20 failure.

21 The question is not whether such a mechanism actually exists, but whether that
22 kind of mechanism is sufficiently plausible to suspend the usual dismissal of feedback
23 regulated growth as a possible mode of evolution. No doubt chaotic variation in an

1 organism's growth limit control system might lead to change in many features at once
2 that might either help or hinder its life support and reproduction. In the normal
3 interpretation of 'mutation and selection', the mutation and selection processes are
4 strictly independent though. It's customary, but is it necessary? By itself the
5 presence of a structure that coordinates growth limits would create a coordinated shape
6 in the organism's potentials, it's 'fitness landscape', opening up and closing down a
7 variety of new potential peaks and pathways. The usual interpretation is that
8 uninfluenced random variation throughout the genome will tend to be reinforced if it
9 moves an organism downhill in such a fitness landscape. The question here is whether
10 such a complex change in an organism's 'fitness landscape' would be accompanied by
11 related variation in the vicinity of the new paths, such as to constitute a kind of
12 exploration, or probing of the landscape. Since this is really all an argument by
13 speculation, looking for what to look for, it seems reasonable to conclude by suggesting
14 that instability in a system's developmental climax control system might have lots of
15 side effects, allowing small increments to move the system either near and far from its
16 present state.

17 *The context of complex systems.* - It may seem as different and difficult as Darwin's
18 proposal for the origin of species was at first, but the various bits of confounding
19 evidence for evolution really make some new idea logically necessary. What is clearly
20 implied by the evidence is that most evolution happens during short periods, by rapid
21 reorganization of a complex distributed system of growth, and that it is logically
22 necessary that it proceed by successively larger and then smaller steps. Growth
23 systems of all kinds and shapes regularly do exactly that. That growth in complex
24 systems has not been studied extensively is not because it has an unimportant role in

1 events. Feedback animated step changes in development are found extensively in all
2 kinds of events, but it's notoriously hard to study, and ultimately requires considering
3 the behavior as developing inside the system exhibiting it. The one thing we know
4 with little doubt is that evolution is a sequential change in the kind of growth climax
5 individuals of a species come to in their own biological development. Perhaps it's
6 reasonable that changes in the form of that growth climax might themselves sometimes
7 develop by growth.

8 'Punctuated equilibria', fit the general model of complex system organizational
9 shifts generally known as 'changes of state'. All of these generally proceed by a growth
10 process and are found in great variety in complex evolving systems (Bak & Boettcher
11 1997). Some disciplines have even demonstrated limited success in modelling them by
12 computer. (Lewin 1999). Complex system level shifts are found in climate & weather
13 systems, politics & social systems, animal behavior, ecologies, electrical discharge,
14 thermal changes of state, etc. We don't understand quite how, but we think nothing of
15 it. The details are always hugely complicated to describe, unfortunately, displaying
16 complex distributed organization most often in the absence of any outside direction or
17 internal record of past experiments to follow.

18 *Possible tests.* - The question is how to test the hypothesis. A single record of
19 speciation by a transient growth process arguably demonstrated here is a small but
20 significant piece of evidence. Where there is one example there may be others. There
21 does seem to be very fine grain behavioral fluctuation behind the irregularity of
22 Malmgren's (1983) data set. Since it's apparently a global species and the fossils are
23 plentiful in hundreds of cataloged ocean sediment cores, it would seem practical to look

- 1 to see which if any of the same fluctuation events appeared elsewhere. Better
- 2 mathematical tests for filtering data sets for those displaying behavioral flow and
- 3 transient dynamics would help to identify other places to look for the same type of
- 4 evidence. It should also be asked whether fossilized plankton contain some genetic
- 5 material. Searches for genetic patterns that change progressively, in step with
- 6 fluctuations in body structure, could possibly hint at the discrete mechanisms involved.

CONCLUSION

For some time it has been understood that most adaptation and invention in evolution occurs at speciation, appearing as gaps in the fossil record that need to be filled by some relatively rapid process of stepwise change.

What has been demonstrated is the use of mathematical techniques borrowed from fractal theory and computer vision and new statistical tests for underlying process flow to solve a stubborn problem of pattern recognition. It would seem likely that the same combination of techniques, distinguishing statistical variation from behavioral variation, followed by curve recognition, could be put to good use elsewhere as well.

The result has been to reveal the underlying behavioral shape of the phyletic succession from G. *pleisotumida* to G. *tumida*. The shape found is a rather familiar one, even if unfamiliar in this context, that of rapid complex organizational change by growth. Malmgren's (1983) conclusion of punctuated gradualism and Bookstein's (1987) interpretation of random walk have both been updated.

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