Repeated Patterns in Behavior and Other Biological Phenomena

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Human environments consist to a large extent of repeated spatiotemporal patterns which are typically composed of simpler patterns. Most humans are thus surrounded by houses, streets, cars, shops, and omnipresent behavior patterns composed of verbal and nonverbal elements. Human individuals are, of course, themselves patterns of parts, such as trunk, head, arms, and legs, that again are composed of simpler parts, and so on, recursively, down to the infinitesimally small. The human individual thus appears as a particular type of repeated pattern immersed in endless numbers of types and instances of other patterns, some man-made and visible, but most neither. This view of human existence is thus in accordance with the words of Francis Crick, one of the discoverers of the structure of DNA: “Another key feature of biology is the existence of many identical examples of complex structures” (Crick, 1989, p. 138).

Regarding behavior, the word identical above might preferably be replaced by the word similar, but molecules also have elasticity (Grosberg and Khokhlov, 1997).

Hidden Patterns

Clearly, the production of patterns and their detection in the behavior of others is essential for communication, and such abilities generally increase during both individual development and phylogenetic evolution.

The ability to recognize patterns in the environment is critical for an organism’s survival. It is a prerequisite for tasks including foraging, danger avoidance, mate selection, and, more generally, associating specific responses with particular events and objects (Sinha, 2002, p. 1093).

The following quotation thus concerns a characteristic of behavior which constitutes a difficult but possibly essential problem for behavioral research: “Behavior consists of patterns in time. Investigations of behavior deal with sequences that, in contrast to bodily characteristics, are not always visible” (Eibl-Eibesfeldt, 1970, p. 1; emphasis added).

In these opening words of his Ethology: The Biology of Behavior, Eibl-Eibesfeldt thus defines behavior as temporal patterns that may occur before the very eyes and ears of observers without being (consciously) noticed.

Emergence

Unexpected and hard-to-explain patterning in nature is receiving increased attention, and interdisciplinary studies of emergence and complexity have gained much momentum (see,
Emergence is often exemplified by Bénard cells, which are particular directly visible patterns that may form on the surface of a liquid that is enclosed in an open container and heated from below (see, e.g., Kelso, 1997, p. 7; Solé and Goodwin, 2000, p. 15). Important aspects of such patterns, which are also among the reasons for being of emergence studies, is that given the available understanding of basic processes, they may be impossible to predict and/or explain.

But while Bénard cells are visible, this is not necessarily the case for all emergent patterns. Or, in the words of James Crutchfield: “It is rarely, if ever, the case that the appropriate notion of pattern is extracted from the phenomenon itself using minimally biased procedures. Briefly stated, “in the realm of pattern formation ‘patterns’ are guessed and then verified” (Crutchfield, 1993; quoted from Solé and Goodwin, 2000, p. 20).

The discovery of patterning may thus require the creation of model patterns with corresponding detection procedures, as will be illustrated below. The study of emergent patterns is closely related to that of self-organization, and emergent patterns in human behavior and interactions are examples of both par excellence.

Obviously, before understanding the function and evolution of any pattern, molecular or behavioral, it must first be discovered. Two pioneers of human interaction research have repeatedly reminded us that that task does not end with the discovery of any fixed number of fully specified patterns: “...a conversation, ... a complex system of relationships which nonetheless may be understood in terms of general principles which are discoverable and generally applicable, even though the course of any specific encounter is unique (cf. Kendon 1963, Argyle and Kendon 1967)” (Kendon, 1990, p. 4; emphasis added).

Unending creativity and uniqueness must thus be expected, and this whirlwind of new combinations may be characteristic of life and the universe itself (Kaufman, 2000).

Hidden Context and Meaning

What if many complex, repeated behavioral patterns are still hidden from the eyes, ears, and tools of researchers? What if some are essential for the understanding of behavior and communication? Moreover, a hidden pattern could be the context which determines the meaning of the simplest elements.

Aiding the Senses

Only adequate models and tools allow the detection of such patterns, and below a pattern type, called the t-pattern, and a detection algorithm (Magnusson, 1996, 2000a) are briefly described, along with examples of discovered behavioral patterns. T-patterns in other
biological phenomena, such as brain-cell interactions, DNA, and memes will be discussed briefly.

**Toward a Model Pattern**

What is a pattern? The broad meaning of the word *pattern* is indicated by the fact that most mathematicians now define mathematics as the science of patterns (Devlin, 1997). Considering behavior as repeated patterns is a long-standing tradition in the behavioral sciences. For example, linguists and ethologists traditionally deal with repeated temporal patterns in communicative behavior, and radical behaviorism deals with probabilistic real-time contingencies (patterns), also with a focus on repetition. Other branches of behavioral science, such as anthropology, social psychology, and sociology, deal with repeated patterns, such as scripts, plans, routines, strategies, rituals, and ceremonies. The importance of repeated temporal patterns in behavior, whether hidden or obvious, is thus widely accepted. But, more formally, what kinds of patterns are they?

**Obvious Versus Hidden Patterns**

The underlying hypothesis here is that many hidden behavioral patterns may be structurally similar to some obvious ones. Characteristics of well-known patterns have thus been combined to create a general-scale independent pattern type. Well-known obvious examples follow:

1. “How are you?” This sequence of words is an *intraindividual* verbal pattern.
2. “How are you?” “Fine, thank you.” This is an *interindividual* verbal pattern.
3. Bill says, “Pass me the salt, Jack.” Jack passes him the salt. This is an *interindividual mixed* verbal and nonverbal pattern.
4. “If... then... else...” This is a verbal pattern with time slots that may be filled in various ways.

A typical dinner is also such a pattern of acts which themselves are patterns—for example: “takes a seat at a table, takes an appetizer, then a main course, then a dessert, then coffee, and finally stands up.” As in “if... then... else...” the number of other acts between the components may vary considerably. Other examples are rhythmic phrases, melodies, and musical themes.

Characteristic of these patterns is the particular order of their components and the particular approximate time distances between them; if the distances are too short or too long,
the pattern disappears or becomes strange or even pathological. Whether a melody or a molecule, it can be squeezed and stretched only within critical limits.

The limited flexibility is generally such that most well-known patterns would hardly ever recur by chance if their components were distributed randomly and independently, each with its own average frequency. This aspect is of essential importance here because hidden patterns are often impossible to detect on the basis of order alone, due to the great variation in the number of other behaviors occurring between their components. This is especially true if the pattern is complex and/or infrequent—occurring, for example, only twice in the data. But the common argument that only frequent behaviors should be studied seems to neglect the fact that the most important events tend to be rare.

Another important aspect for detection is hierarchical structure, often with many levels, since pattern components may themselves be patterns of still simpler patterns. For example, a common phrase is composed of words that are composed of syllables. And its words may occur in various other phrases and even alone. Similarly, its syllables may occur in other words and possibly alone.

A multitude of common rituals, ceremonies, routines, conferences, classes, financial operations, and even genes and genomes seem to correspond to the defining characteristics of this general one-dimensional “flexible” pattern type.

T-Patterns Are Often Hard to See

The slightest presence of behaviors other than those pertaining directly to a t-pattern can make the most regular t-pattern invisible even in the simplest data, as is shown in figure 7.1. Similar difficulties are encountered when searching for such patterns in video recordings of behavior, even after they have been pointed out. Overlapping patterns unfolding over many time scales and modalities may simply be too much to follow. This, combined

![Diagram of T-patterns]

Figure 7.1
T-patterns are easily overlooked. The letters a, b, c, d, and k represent occurrences of event types A, B, C, D, and K on a single dimension. The lower axis and its data are identical to the upper one except that occurrences of events of type K have been removed, making the two hidden occurrences of the simple t-pattern (A B C D) appear clearly.
with the well-known human tendency to see patterns where there are none, calls for improved means of detection.

**Derived Types and the T-System**

The following are some of the terms which have been derived from the t-pattern type and together form the t-system:

The *t-marker* is a component of a t-pattern that rarely occurs independently of that pattern and thus indicates its presence (Magnusson and Beaudichon, 1997).

A *t-associate* (+/−) of a t-pattern Q is not a component of Q, but is behavior (event type or pattern) that has a significant positive versus negative tendency to occur (anywhere) during or near occurrences of Q. It may thus serve as an indicator of the occurrences of its associate pattern. A *t-satellite* of Q is a positive t-associate that always and only occurs together with Q, while a *t-taboo* is a negative t-associate of Q that never occurs with Q. *T-drifters* are behaviors belonging to none of the other categories of the system.

A t-pattern with its +/- associates is called a *t-packet*, and it has an attraction and a repulsion zone around it defined by the occurrence/nonoccurrence of its +/- associates.

*T-coverage* of a pattern is the total amount of time the pattern is in progress; it is called percent coverage when expressed as a percentage of total observation time.

*T-composition* is the set of alternating nonoverlapping patterns with the highest combined t-coverage in a given data set.

**Origin of the T-System and Theme**

The conceptual and algorithmic development behind the t-system and Theme (the t-pattern detection program, Magnusson, 1996, 2000) was initially stimulated by research regarding the structure of behavior and interactions with varying focus on real-time, probabilistic, and functional aspects, as well as hierarchical and syntactic structure, creativity, routines, and planning (notably, Chomsky, 1959, 1965; Cosnier, 1971; Dawkins, 1976; Duncan and Fiske, 1977; Miller et al., 1960; Montagner, 1978; Skinner, 1957; Tinbergen, 1963).

**Method**

The t-pattern detection algorithm, which performs a fully automatic search for t-patterns, is based on a formal definition of t-patterns relative to a particular data structure, the t-data set.
T-Data Sets

Each of the behaviors or acts that may occur in a pattern is here called a behavior type. When the actor is also specified and whether it is the beginning or ending of the behavior, the term event type is used. For example, “Bill begins walking” (or, in short form: bill, b, walk) is an event type which may also be further qualified (e.g., bill, b, walk, fast). The behavior is coded in terms of the occurrence times of such beginnings and endings (points) on a discrete time scale. Each beginning and/or ending thus either occurs or does not occur at a discrete time point. Any number of event types (involving any number of actors) may occur at the same discrete time point (i.e., basic time unit). The occurrences of each event type within the continuous observation period(s) thus constitute a time point series (or process (see, e.g., Daley and Vere-Jones, 1988).

The real-time behavior record is thus a data set consisting exclusively of such series of occurrence times (i.e., a multivariate point process) and a specification of the observation period(s). Below, all definitions of t-patterns and any derived terms refer exclusively to such data sets (see example in figure 7.2). It goes without saying that all results still depend on insightful choice of categories and careful coding.

T-Pattern Definition

The following notation expresses more formally the general structure of any given t-pattern with m components:

\[ X_1 = dt_1 \quad X_2 = dt_2 \ldots X_i = dt_i \quad X_{i+1} \ldots X_{m-1} = dt_{m-1} \quad X_m \]

The \( X_1 \ldots X_m \) terms stand for pattern components, which may be either event types or other t-patterns (recursive definition). The \( \approx dt_1 \ldots dt_{m-1} \) terms stand for the approximate characteristic distances between the consecutive components. The general term \( X_i \approx dt_i \) \( X_{i+1} \) thus means that component \( X_i \) is followed within the approximate characteristic time distance \( \approx dt_i \) by component \( X_{i+1} \).

That is, over a given number of occurrences of a pattern within a given observation period, each \( \approx dt_i \) varies within an interval given by its lowest and highest values, here noted as \([d_{1i}, d_{2i}]\). The general term \( X_i \approx dt_i \) \( X_{i+1} \) may thus be rewritten as

\[ X_i [d_{1i}, d_{2i}] X_{i+1} \]

which means that component \( X_i \) is followed within time window \([d_{1i}, d_{2i}]\) by component \( X_{i+1} \).

T-Patterns as Critical Interval Trees

For detection purposes, binary tree representations of any t-pattern can be obtained by splitting the t-pattern into two parts (left and right) and then, recursively, splitting each
side down to the terminal event type level. For longer patterns this can be done in numerous ways. (Note also that any subpattern or branch of a t-pattern may occur more frequently than [i.e., independently of] the full pattern.)

The first rather loose t-pattern definition can then be replaced by a more restricted definition of the t-pattern as a binary tree of critical intervals, each relating a left (preceding) and a right (following or concurrent) part. In this way, any given t-pattern (and any of its subpatterns) can be written as a pair of components related by a characteristic (or critical) interval:

$$X_{\text{left}}[d_1, d_2]X_{\text{right}}$$

Here, $X_{\text{left}}$ stands for the first part, ending at $t$, which is followed within the critical interval $[t + d_1, t + d_2]$ by the beginning of the latter part, $X_{\text{right}}$, where $0 \leq d_1 \leq d_2$. (The $t$ is implicit in $[d_1, d_2]$, but omitted to simplify notation.)

**The t-Pattern Search Algorithm**

In behavior records of a moderate size (e.g., 100 event types, each occurring at least twice), the number of possible patterns involving, for example, ten event types is astronomical; since both sequence and interval length variation are considered, it is far greater than $100^{10}$. Even for much smaller data sets the number can be staggering.

Trying out all possible sequences of all possible lengths is clearly not an option. Instead, the proposed search algorithm can be said to reverse the above top-down recursive splitting of a given t-pattern with known critical intervals, ending with event types as the (linear) string of leaves (or terminals) of a binary tree of critical intervals. The algorithm thus begins with only a data set of event type series possibly containing t-patterns, and it attempts to construct (detect) such binary t-pattern trees. Rather than trying out all possible combinations, it works bottom-up, level by level, first searching for the simplest possible t-patterns, which at the lowest hierarchical level are pairs of directly coded event types having a critical interval relationship.

This relationship, a case of $X_{\text{left}}[d_1, d_2]X_{\text{right}}$, is detected by a special algorithm which considers all possible pairs of components as possible $X_{\text{left}}, X_{\text{right}}$ parts. It thus measures the time distances from each occurrence of $X_{\text{left}}$ to the first following or concurrent occurrence of $X_{\text{right}}$. Using this distribution, it searches for the longest possible interval $[d_1, d_2]$ such that $(X_{\text{left}})$ (ending at $t$) is, significantly more often than expected by $h_0$, followed within $[t + d_1, t + d_2]$ by the beginning of another component $(X_{\text{right}})$. Here $h_0$ is that $(X_{\text{right}})$ is independently and randomly distributed over the observation period $[t_1, t_2]$ with a constant probability per time unit: $N(X_{\text{right}})/(t_2 - t_1 + 1)$, where $N(X_{\text{right}})$ is the number of occurrences of $X_{\text{right}}$. 


When they are found, the algorithm connects the critically related instances of each of the two components and adds them to the data as the occurrences of a newly detected t-pattern, which later in the process may become a (left or right) component in a more complex pattern. Gradually, longer patterns may thus be detected as patterns of already detected patterns.

As indicated above, each t-pattern of some length \( m > 2 \) may be represented as a binary tree in various ways: for example, ABCD as \(((A (B C)) D), ((A B)(C D)), (((A B) C) D))\, and so on. Similarly, complex t-patterns existing in the data may be detected (constructed) in many different ways, and this can easily lead to numerous partial and/or redundant detections of the same underlying patterns. The primary objective here is to discover the most complete (most complex, and thus a priori most unlikely) t-patterns; therefore, all detected patterns are automatically compared with all the others, and patterns that occur only as parts of more complete (complex) patterns are dropped.

The detection process stops when no more critical relationships can be found, given the specified significance level. At very low significance levels none are found. At a higher level (an approximate “ideal” level, often near 0.005) all the most complex patterns are detected, and at still higher levels the same patterns are more redundantly discovered as more and more binary trees become significant for each underlying pattern (see Magnusson, 2000). Through this process of pattern growth (construction) and competition for maximum completeness, complex patterns often evolve. They constitute the output of the search process and are typically invisible to unaided observers.

**Statistical Methods and t-Patterns**

The initial t-pattern algorithms (Magnusson, 1982, 1983, 1988) were developed after carefully considering the use of standard statistical methods for behavior analysis (see, e.g., Colgan, 1978; Monge and Cappella, 1980; Scherer and Ekman, 1982). Such methods, which are implemented in the major statistical software packages and in some specialized behavior analysis software (for example, Bakeman and Quera, 1995; Noldus, 1991), do not allow the detection of complex t-patterns and were not developed for that task. Actually, none of the following essential elements are provided: the t-pattern definition, automatic critical interval detection, multilevel bottom-up pattern construction, and completeness competition. The Theme t-pattern detection program (Magnusson, 1996, 2000) is thus quite different from these, but has some similarity with the so-called evolution programs (Michalewicz, 1996).

**Research Application**

T-pattern detection can have two quite different aims. One is to detect effects of external (experimental, independent) variables on behavior. It has been shown that various aspects
of t-patterns, such as the number and types of behaviors and actors involved, may vary strongly with independent variables even when no such effects on event type frequencies or durations are found using traditional statistical methods. A different use of t-pattern detection is aimed at the deepest possible understanding of the structure of each stream of behavior or interaction, but many studies have involved both approaches. (See, e.g., Beaudichon et al., 1991; Blanchet and Magnusson, 1988; De Roten, 1999; Grammer et al., 1998; Hirschenhauser et al., 2002; Lyon et al., 1994; Magnusson, 2000b, 2003; Magnusson and Beaudichon, 1997; Martaresche et al., 2000; Martinez et al., 1997; Merten, 2001; Montagner, et al., 1990; Schwab, 2000; Sevre-Rousseau, 1999; Sigurdsson, 2000; Tardif and Plumet, 2000; Tardif et al., 1995.)

In particular, t-patterns may reveal cycles not present in any of their component series (Magnusson, 1989). Attempts have been made to represent the structure of particular types of encounters in terms of a kind of (flowchart, graph) “grammar” based on the t-patterns detected within them (Duncan, 2000). (For other references and information concerning t-patterns and Theme, see www.hi.is/~msm, www.patternvision.com, and www.noldus.com).

Results

A few t-patterns detected in different types of human interactions will be presented here. The main purpose is to show that complex t-patterns may be hidden in behavior and that they can be detected with the t-pattern algorithm.

All critical intervals of all presented patterns were significant at 0.005 or lower, and only far simpler nonsense patterns were found when the data were randomized before the search. The randomization of a whole data set here consists of simply replacing the occurrence series of each event type with a series containing the same number of points dispersed randomly over the observation period.

Reading the t-Pattern Diagrams

Figure 7.2 shows the data set in which the pattern presented in figure 7.4 was detected. Each horizontal line of points in figure 7.2 thus shows the occurrence times of one of its 53 event types. The pattern in figure 7.3 was detected in an equally opaque data set (not shown, to save space).

The three-box t-pattern diagram, as shown in figures 7.3 and 7.4, was created for the visualization of various aspects of detected t-patterns, especially the way in which they were gradually detected, bottom-up and level by level. The focus is thus on the hierarchical critical interval relationships between the occurrence series of the event types that
make up the t-pattern. It also shows the way in which particular points in each series are connected to form each instance of the pattern. There are three main boxes.

**The Top-Left Box** shows all the event types (i.e., $X_1 \cdots X_m$) of the pattern and how they are gradually connected, level by level, into the full binary tree t-pattern. For example, in figure 7.4, at the first level, (2) connects to (3), forming pattern (2 3), and (4) connects to (5), forming pattern (4 5). At the second level two patterns are also formed: (1) connects to pattern (2 3), forming pattern (1 2 3), and pattern (4 5) connects to (6), forming pattern ((4 5) 6). Finally, at the third level the patterns (1 2 3) and ((4 5) 6) are connected to form the full pattern shown in figure 7.4: (1 (2 3)) ((4 5) 6).

**The Top-Right Box** Immediately to the right of each event type in the top-left box, the occurrence series (from the data set) is shown. Connection lines also reveal how the particular critically related occurrences of the event types and/or subpatterns are connected,
Figure 7.3
Interactive t-pattern detected in two five-year-olds, X and Y, playing for 13 min with a picture viewer. B = begins; E = ends. Behaviors are automanipulate = fiddle with something without watching it; haveviewer = have the viewer; order,viewer = order the other to give up the viewer; view, long = look in the viewer for >3 seconds; lookat,partner = looks at the other; lookat,picturecard = looks at a picture card that’s not in the viewer; manipulate,viewer = manipulates the viewer. Time is in video frames, 1/15 s.

level by level, to gradually form the complete pattern. (In this box, occurrences of sub-patterns that sometimes occur outside the full pattern are also shown.)

The Lower Box shows the occurrences of the full t-pattern tree on the real-time axis in a manner similar to the lower part of figure 7.1, but without the letters. Note that when event types occur simultaneously within a pattern, lines overlap and the branching becomes invisible, but can still be seen in the top-right box.

Pattern Example 1

This interactive pattern (figure 7.3) was found in a 13-min dyadic interaction between two five-year-old children who took turns playing with a picture viewer and a few picture cards
Their behavior was coded using a preexisting list of categories (McGrew, 1972) with a few additions related to the particular situation. Unexpectedly, a very regular t-pattern with 25 event types was found, and the total duration of its four occurrences was >90 percent of the total observation time. However, no verbal acts had then been coded. When the occurrences of the verbal act “(begins) order the other to give up the viewer” (i.e., b, order, viewer) was tentatively coded for both children, the t-pattern shown in figure 7.3 was discovered. (Only beginning coded, due to the short event duration.) It is not the most complex pattern detected in this interaction, but it is presented here in relation to the point made above: that the meaning or function of a simple behavior may depend on its relationship to a (here multimodal) hidden pattern.

The “order, viewer” behavior of one of the two children is the fifth event type of this pattern—(5) in figure 7.3—and clearly may be left out without noticeably affecting this t-
pattern or its detection. The causal effect of “order, viewer” is therefore in doubt, and each pattern occurrence is predictable from well before the “order, viewer” behavior occurs until the final event type (22). However, the event type “x, b, order, viewer” also occurs twice outside the pattern (see figure 7.3), in both cases possibly a bit too early to be effective. In any case, it seems likely that expectations are building up in each child relative to the “meaning” of each act performed by the other within this repetitive and highly patterned context.

**Pattern Example 2**

The interactive pattern example shown in figure 7.4 was found in one of the dyadic interactions coded in a study of children’s collaborative (dyadic) problem solving (see, notably, Beaudichon et al., 1991; Magnusson and Beaudichon, 1997). A total of 538 occurrences of 53 different verbal and nonverbal event types occurred in this particular 25:07 min dyadic interaction between children E and N (see the data set in figure 7.2).

As can be seen in figure 7.4, the three occurrences of the pattern are in progress during most of this 25-min interaction. Each pattern occurrence consists of the following acts (where b stands for “begins”; only the beginning points of these brief acts were coded):

1. E, b, ord, tac: E gives an order (ord) concerning task (tac), and is followed within 5 to 7 s by
2. N, b, fou, tac, nv and, simultaneously,
3. N, b, fou, tac: N provides information (fou) concerning the task both nonverbally (nv) and verbally (default). Then, each time (!), 4:00 to 4:04 min later,
4. N, b, que, reg, nv: N asks a question (que) regarding a solution rule (reg) nonverbally (nv), 14–18 s later by
5. E, b, evp, s: E makes a positive evaluation (evp) of task performance, talking to herself (s). Finally, 2:02 to 2:05 min later,
6. E, b, ord, tac: E again, as in (1), gives an order concerning task execution (actually a series of orders, as can be seen in figure 7.4), and the whole pattern (again) follows. (1) and (6) are thus the same, but different instances are involved. This pattern, which involves 5 of the 53 series in the data set, thus revealed a deep, unexpected, and invisible temporal structure in this complex 25-min encounter.

**Discussion**

Hidden t-patterns seem common in human behavior and interactions, and interacting humans tend to construct complex patterns and then repeat them in a similar way within
each interaction. The production and perceptual detection of such patterns may well constitute important social skills to be considered in studies of, for example, human social handicaps and “social” robotics.

**Genes and Genomes as t-Patterns**

The so-called backbone of the DNA molecule is a cyclical structure of alternating molecules (somewhat like a ticking clock or markings on a scale) with a base pair occurring at each cycle. Each gene is a particular pattern of such base pairs along the DNA molecule (but see, e.g., Keller, 2000), and in complex organisms such as *Drosophila* and humans, each gene is composed of two alternating patterns called introns and exons. When a gene is transcribed into a protein, only the exons are used, but the noncoding introns define distances between the exons characteristic for the gene much as the characteristic distances (\(\approx dt\)) separate the components (event types or patterns) in t-patterns. The DNA gene sections are again separated by noncoding sections, so the whole genome can be seen as a massively repeated t-pattern within the organism, influencing all its functioning. Introns are not present in bacterial genes (Griffiths et al., 1999, p. 33), and it is tempting to ask whether an analogy might exist in the evolution of behavioral and communication patterns. A search for t-patterns in DNA, RNA, and proteins is now in progress in collaboration between the author and researchers at Decode Genetics, Inc., Pattern Vision Ltd., and the University of Paris VII (Icelandic Research Center, grants: 013220001 and 013220002).

**T-Patterns, Writing, and Memes**

Writing transformed vocal verbal behavior into relatively durable objects independent of the producers, and thus created a revolution in human behavioral possibilities especially after the invention of the printing press—without which modern science and technology would hardly exist. Through writing, speech sound t-patterns are translated from the single dimension of time to that of a string of symbols on a page that, like the DNA molecule, are much more durable than the sounds. Both these types of relatively durable strings thus bring about, from within rather than from outside, some approximately predictable effects on individual behavior.

A multitude of “cultural genes” or *memes* (notably, Blackmore, 1999) seems to depend on relatively durable t-patterns. Bibles, constitutions, and many other standard word sequences are examples of such “t-meme” objects that influence human communities in somewhat the same way as molecular sequences (genomes, genes, proteins, or pheromones) influence organisms or insect societies. Noticeably, like cells, different categories of human individuals are known to focus on or use different (sections of) standard texts.
Toward Pattern Bases

For studies of evolution, databases of detected behavioral patterns need to be easily accessible—for example, through the Internet, as is already the case for molecular sequences within genetics (see, e.g., Attwood, 1999; Gibas and Jambeck, 2001). The creation of such a pattern base is in preparation in the context of a collaborative project between the author and Dr. Benjamin Isaac Arthur, Jr., at the Biology Department of Brandeis University, where numerous t-patterns have just been discovered in *Drosophila* courtship interactions.

Brain Behavior

Since the brain provides the moment-to-moment control of human behavior, it seems reasonable to guess that the temporal organization of its activity might be at least somewhat similar to that of behavior. Or, in the words of Scott Kelso, “In fact, the claim of the floor is that both overt behavior and brain behavior, properly construed, obey the same principles” (Kelso, 1997, p. 28).

Recent technological developments now allow concurrent registration of multiple related brain cells (see, e.g., Rieke et al., 1997), and thus the possibility exists of finding t-patterns in cell interactions. The very first such search has been carried out. A multitude of complex intercell t-patterns was detected, but further systematic study is in progress (in collaboration between the author and Dr. Alister U. Nicol, Laboratory of Cognitive Neuroscience, Babraham Institute, Cambridge, U.K.).

Facing Behavioral Complexity

Behavioral scientists have had their hands full with the study of directly visible/audible behavior, and have paid less attention to hidden repeated patterns, probably in part due to the rarity of adequate models and tools—a kind of vicious circle. At least within psychology the situation has not been favorable: “Only about 8% of all psychological research is based on any kind of observation. A fraction of that is programmatic research. And, a fraction of that is sequential in its thinking” (Bakeman and Gottman, 1997, p. 184).

Within social psychology, a similar situation has prevailed regarding the temporal aspect of behavior (McGrath, 1988). And ethology students are still taught little about structural analysis except the simplest kinds of sequential analysis, which easily miss the rich complexity of behavior and often produce more frustration than insight. One wonders what might be the state of, for example, chemistry under similar constraints.

Computers versus Nervous Systems

Computers already turn out to be inferior or superior to humans, depending on the nature of the task. Thus, for example, highly regular t-patterns easily escape the attention of
humans, while a relatively simple special-purpose algorithm can find complex t-patterns even when large numbers of other behaviors occur in parallel. Still, the t-pattern type seems to correspond to a large class of biological patterns that are especially common in communicative behavior. Is the nervous system constantly more or less overloaded as it simultaneously considers too many possibilities? And how much is it possibly detecting at the unconscious level?

**Conclusion**

The creation of new model patterns with corresponding detection algorithms is needed to allow new insights into the hidden complexity of behavior and communication processes. This will undoubtedly continue to require considerable interdisciplinary collaboration, including the relatively new fields of complexity and bioinformatics. I hope that, a kind of future “ethomatics” will help bring to light the true complexity and evolution of biological communication systems.

**References**


