G. Riva, M.T. Anguera, B.K. Wiederhold and *F. Mantovani* (Eds.)
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6 Structure and Communication in Interactions

Magnus S. MAGNUSSON

Abstract. The highly demanding study of meaning, intention, and communication including miscommunication, in human interaction seems to call for the development of powerful new approaches and in that context the astonishing raw power of modern computers may eventually be harnessed, given that adequate models, methods, algorithms and software be developed and made available. In this context, a proposed data structure, pattern definitions, algorithms, and a new statistical validation test are proposed. New additions are introduced to this theoretical/methodological system (called t-system) including special definitions of well known phenomena such as bursts and cyclical occurrence as well as of more novel concepts called "t-blocks", "t-metronomes" and "ghost cycles". A method is introduced to deal with the estimation of a priori probability (or statistical significance) of individual patterns without consideration of the arbitrary binary trees used for their detection and in this context "t-templates" and their matching are introduced. Statistical validation through shuffling of data is compared with a suggested method called (random series) rotation (t-rotation) and results obtained with each are compared for both human and neuronal interactions. It is pointed out that brain behavior as observed with brain scanners does not offer direct insight into meaning and intentions, but essentially means more behavior to observe and more patterns to be detected, while limitations in social neuroscience seem to repeat to those of earlier human interaction studies and also due to technical difficulties. Finally some thoughts and questions are put forward concerning possible relations between on one hand hidden patterns and symmetry in interactions and on the other hand meaning, intentions, communication and miscommunication in highly patterned human interactions as well as about the possible need for new and specialized mathematics for the study of these phenomena.

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6.1 Introduction

Patterns in behavior are frequently hidden from the consciousness of those who perform them as well as to unaided observers. Considering this as a fact, the approach outlined here is about defining and discovering repeated temporal patterns in behavior with a special focus on interactive behavior. For this, algorithms have been developed as a kind of "seeing aids" somewhat like eye-glasses, microscopes, telescopes, sonar and various other instruments.

This approach has often led to the discovery of unexpected patterns some of which have been surprising and have often elicited the questions "But what does it mean?" referring to some particular detected pattern, or more generally, "What do they mean?" referring to many or all such patterns. Especially when no clear meaning is given to the term "meaning", answering such questions is no simple matter, but it seems that very strong demands in this direction are not always justified given the present level of understanding of human behavior and interactions. On the other hand, discovering previously unknown repeated patterns or symmetry is often considered a major goal and achievement in sciences such as physics (see below) and biology (for example, the discovery of the double helix) even before anything can be said about their "meaning" not to mention any kind of "intentions" behind their existence.

It has been said that in its rush to become a respectable science, psychology neglected its natural history phase, a part of which is to find out what phenomena exist and need explanation within the particular field of research. In astronomy such phenomena now include galaxies and galaxy clusters, which were at best only dots of light for the early unaided observers who frequently assigned all kinds of meaning and intentions to what little they could possibly see. Extensive regularities in the movements of various kinds of heavenly bodies were only discovered after thousands of years of systematic observation and record keeping, but neither meaning or intention have really been found even if many have bee assigned. No more than, for example, in the repeated interaction patterns or symmetries within the nuclei of atoms discovered through great efforts by a large number of highly trained specialists using extremely expensive instruments as in the case of, for example, leptons and quarks:

"So, it's simply not yet understood why, if there are three generations of leptons, there should necessarily be precisely three generations of quarks. It could just be an accident of nature, but past experience suggests that a symmetry pattern as simple and clear as this provides an essential, if yet undeciphered, clue about the workings of nature." ([1], p. 118).

Accounts of the concept of symmetry and its use as well as of the closely related Group Theory are easily available (for example, [2-4]).

6.2. Brain-patterns and Human Interaction

When the present repeated pattern discovery approach was adopted in the early seventies with a strong desire for objectivity, no real access was available to the inner

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events of the active human brain and intentions could only be inferred from observable verbal and nonverbal behavior including self-reports such as individuals' introspections about their own intentions and behavior. However, people often being unconscious about their intentions and how they communicate or bring about the corresponding wanted changes in others, self-report is known to be unreliable scientific evidence. Making inferences about others intentions on the basis of direct observations of their behavior, on the other hand, is usually colored by projections and general lack of context and situation awareness by the observer. These difficult matters related to conscience, intensions, miscommunications (see notably, [5]) will be briefly reconsidered at the end of this paper after considering some issues and results regarding patterning and its detection in interactive behavior.

As a mater of fact, there seems to be no easy track around these difficulties as context is so decisive for meaning and effect and frequently extends in such complex ways in time and space. Even now in times of brain scanners and imaging, although still mostly applicable to immobile individuals rather than to natural interactions, such information calls for non-obvious interpretations.

"Despite the impressive amount of research generated, social cognitive neuroscience is still in its infancy and has so far focused on the study of very basic social abilities… The simplicity of the studies to date may reflect the early stage of development of the field and the methodological limits imposed by neuroimaging and other neurophysiological techniques." ([6], p. xvii.)

So, in spite of the spectacular methodological progress offered by brain scanners they still do not provide direct access to conscious and/or unconscious meanings or intentions. Finding out with certainty what is "really" going on even in the simplest dyadic encounter is therefore still far beyond easy scientific reach. As brain scanner technology enters the realm of communication research, familiar concerns seem to resurface:

"Most of the neuroimaging studies that investigate social phenomena do so from a uni-directional perspective. The focus has been on understanding the effects of socially relevant stimuli on the mind of a single person. In contrast, the study of social interaction involves by definition a bi-directional perspective and is concerned with the question of how two minds shape each other mutually through reciprocal interactions." ([6], p. xvii.)

These concerns recall the evolution within psychology from "interaction studies" focusing on just one individual within an interaction to a focus on the interaction as an organized whole where both or all parties have to be considered together, that is, at the same time and as a single system. Before film or video it was difficult to fix the object of study for thorough analysis and when that problem was solved there came the difficulty of analyzing by hand the complex resulting data so that the analysis of painstakingly established real-time behavior records mostly concerned frequencies and durations of the behaviors. With computers such analysis was made extremely quickly, but no methods or software were available for relevant deeper analysis specially aimed at real-time behavioral data. Often methods and software were used that had been developed for very different purposes, even those intended for the analysis of questionnaire data rather than the real-time event-streams of

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interactive behavior. For those who wanted to delve deeper into the obscure structure they sensed before their eyes, no special purpose tools were available.

Technological and related methodological progress thus has long been a shaping factor in interaction and communication research. The future possibility of integrating behavioral data and data from ever more advanced brain-imaging technology that would amongst other allow scanning brain activity in freely moving individuals is certainly a stimulating perspective. But such technology also produces complex real-time streams of brain-events, which probably also form patterns that need to be discovered and interpreted in relation to other types of events and patterns and possibly at least some of the temporal patterning within the brain may be similar to that of the behavior it produces.

Unfortunately, observation of the active brain has not provided access to any kind of "little man" who can tell what is really going on and modern brain scanners only find more behavior and more, not less, behavioral patterns to discover. Application of t-pattern analysis to interactions within populations of neurons in living brains is in progress [7].

It has been the philosophy of the present pattern definition and detection approach to keep things as simple as possible for a number of reasons. One main reason is that mathematically/statistically complex methods tend to be misunderstood and/or misused if not simply (and often wisely) ignored. It also seems a reasonable pursuit to make available behavioral research models, methods and tools that can be fully understood and used without years of special mathematical/statistical preparation which is often impossible to include in either university studies or research carriers. Furthermore, approximation is here chosen when greater precision lies beyond available resources or represents uncertain scientific gain.

6.2.1 The Data Structure

The t-pattern model described below refers to a set of event-types $E = \{e_1, e_2, e_3...\}$ and their respective occurrence time point series $S = \{s_1, s_2, s_3...\}$ within a continuous observation period (1, T) of T discrete time units; where e_i has occurrence time series s_i.

The event-types in E typically stand for the beginning or ending of some behavior by an actor (agent, system, etc.). For example, "Sue begins running" and "Bill ends laughing" are event-types and are here noted as "sue,b,run" and "bill,e,laugh". Similarly, the event-type "neuron 12 fires" may be noted simply as, for example, "n12", since a spike may be considered too short for coding its beginning and end separately and since firing may be all that is registered for a neuron. The coded behavior records thus consist of the occurrence time series of such types of events so a data set, D, therefore really consists of a set of labeled series: $D = \{(e, s)_1, (e, s)_2, (e, s)_3 \ldots\}$ and the observation time, T.

Such data is called t-data and is the basic reference for all definitions in the t-pattern system which integrates a growing number of structural types aimed at the analysis and description of behavior. Figure 1 shows a real example of such data, below referred to as *Data1*, including 82 event-type series resulting from the coding of approximately 13:30 min of dyadic toy-play and toy-exchange interaction between five-year-olds. A previously published [8] list of categories for ethological analysis of children's behavior with a few additions, was used for the coding that was carried

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out using a digitized 15 frames per second video recording and an interactive multimedia computer program.

As a matter of fact, the definitions only refer to S and [1, T] and the corresponding elements in E are only seen as series labels or names. However, once patterns have been detected they can be selected and analyzed on the basis of information contained in the labels.

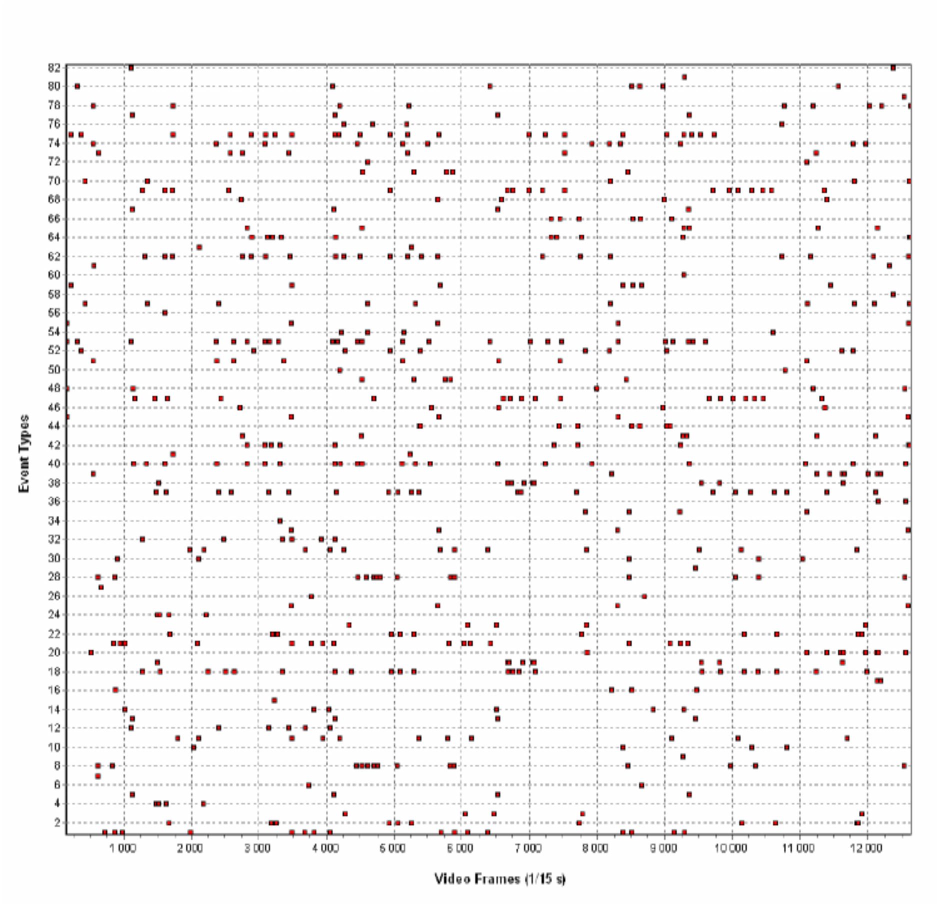

Figure 1. This figure shows all the occurrence time points of each of the 82 event-types coded in a 13.5 min toy-play & toy-exchange interaction between two five-year-olds. The occurrence times for each of the 1 to 82 event-types can thus be read from left to right across the chart. The event-types are listed in the order indicated in the Appendix. This data set is referred to as *Data1*. The event-types with their meanings are listed in the Appendix.

Analysis of data of this kind has often focused exclusively on the number of occurrences (frequency) of the event-types or of the durations of the periods from their beginnings to their ends (i.e., from sue,**b**,run to sue,**e**,run). This could be a demanding task when it had to be done by hand, but usually is now done in less than a second on a PC. Figure 2 shows the result of such analysis of *Data1* (shown in Figure 1) and indicates the limited information it provides about the real-time patterning of the interaction.

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The number of other kinds of relationships that may exist between the points in S is infinite and exploring but the simplest is impossible by hand. As a matter of fact, such tasks can be very hard or even impossible using high speed computers. For example, given data with 100 series, considering all possible temporal patterns each involving up to all 100 of is such a task. Blind and unlimited search for any and all kinds of patterns even in the most ordinary kind of real-time behavior records is therefore doomed even if it made sense.

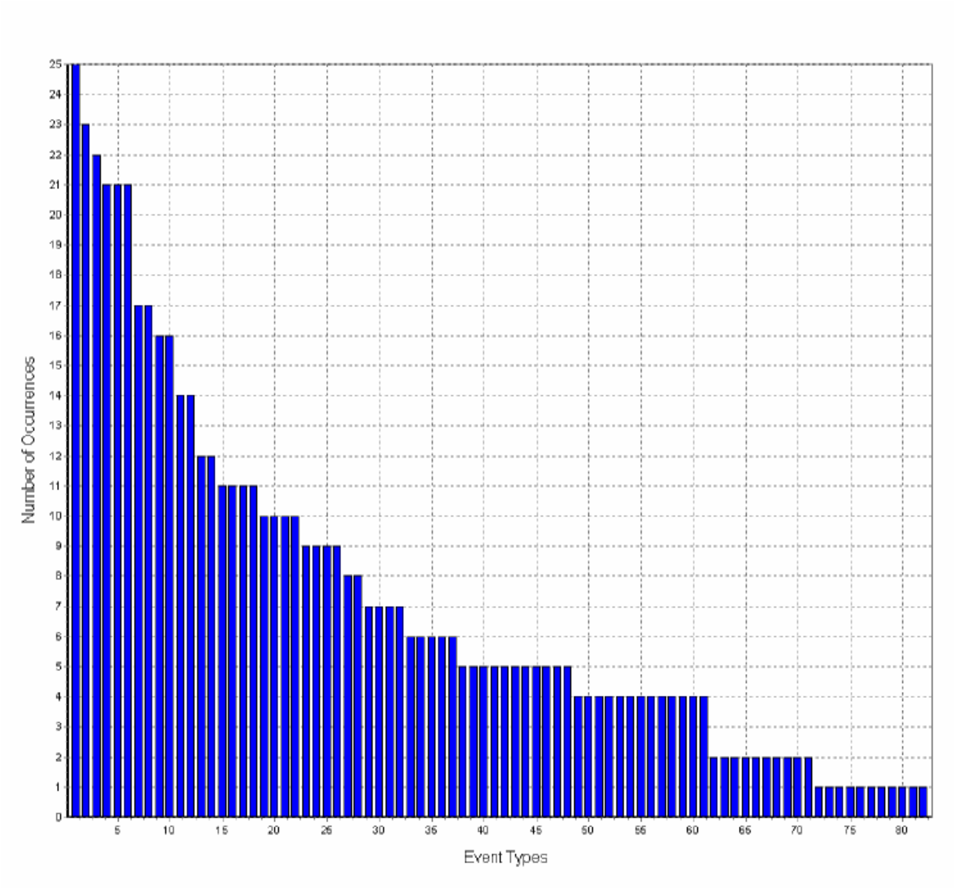

Figure 2. This figure shows the frequency distribution for the 82 event-types in *Data1*. The event-types are listed in the appendix.

To instead harness the amazing power of the modern PC now everywhere present and frequently idle, formalized ideas regarding things to look for are necessary.

A particular kind of structure, called a t-pattern and some derived aspects that together are called the t-system, have been proposed in this context and are described in detail elsewhere and various applications cited [9-12] but short descriptions will be presented below. Some new additions to the system will also be described and illustrative results of their application in the analysis of interactions presented.

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6.2.2 The T-pattern

A t-pattern is basically a set of event-types occurring concurrently and/or sequentially with **significantly invariant** time distances between each consecutive pair within the pattern, which can be noted in the following way:

I) $X_1 \approx dt_1\ X_2 \approx dt_2\ X_3 \ldots X_i\ \approx dt_i\ X_{i+1} \ldots X_{m-1} \approx dt_{m-1}\ X_m$

Where each X term stands for some element of E (some event-type) and the general term $X_i\ \approx dt_i\ X_{i+1}$ means that during occurrences of the pattern, consecutive terms X_i and X_{i+1} are separated by the characteristic approximate time distance $\approx dt_i$.

The meaning of the term “significantly invariant” above must, of course, be defined formally amongst other for detection purposes using automatic computational algorithms.

For this purpose I) above is replaced by a consideration of the variation limits of each $\approx$dt term, that is, the intervals between the lowest and the highest value of each $\approx dt_i$ within a given observation period (data set):

II) $X_1\ [d_1, d_2]_1\ X_2\ [d_1, d_2]_2\ X_3 \ldots X_i\ [d_1, d_2]_i\ X_{i+1} \ldots X_{m-1}\ [d_1, d_2]_{m-1}\ X_m$

Where the general term $X_i\ [d_1, d_2]_i\ X_{i+1}$ now means that within occurrences of the pattern, after an occurrence of X_i at t there is a time window $[t+d_1,\ t+d_2]_i$ within which X_{i+1} will occur. (Here, m is called the <u>length</u> of the pattern.)

To be truly useful for the detection of complex hierarchical patterns, the d_1 and d_2 parameters of each interval must be detected and the pattern detection process must be done bottom-up to be computationally feasible. For this purpose a binary tree structure is imposed such that a particular pattern of type II) above, for example,

$A\ [d_1, d_2]_1\ B\ [d_1, d_2]_2\ C\ [d_1, d_2]_3\ D$

can be seen as the terminal string of one or more such a trees, for example,

$((A\ [d_1, d_2]_1\ B)\ [d_1, d_2]_2\ (C\ [d_1, d_2]_3\ D))$ or
$((A\ [d_1, d_2]_1\ (B\ [d_1, d_2]_2\ C))\ [d_1, d_2]_3\ D))$ or $(A\ [d_1, d_2]_1\ (B\ [d_1, d_2]_2\ (C\ [d_1, d_2]_3\ D)))$

In this way the $[d_1, d_2]$ can be seen as a binary relation between the two branches at each non-terminal node of the pattern. Significant invariance in the distance between any two branches is here defined on this basis and only trees with such a relation at each non-terminal node are t-patterns by definition. Between any two point series (as those in S), s_a and s_b, a particular relation is thus defined called a critical interval relation, $R(s_a, s_b, c, d_1, d_2)$, where c is the pre-specified level of significance and $[d_1, d_2]$ is the critical interval that needs to be detected. For the series s_a and s_b (respectively, noted as t_{ai} ; $i=1..N_a$ and t_{bj} ; $j = 1..N_b$) this relation exists, per definition, if for significantly more of the intervals $[t_{ai} + d_1, t_{ai} + d_2]$ than expected by chance, there is at least one point t in s_b such that $t_{ai} + d_1 \leq t \leq t_{ai} + d_2$; where $0 \leq d_1 \leq d_2$, and $[d_1, d_2]$ is the largest interval for which this is true, and N_a and N_b are, respectively, the number of occurrences of event-types e_a and e_b.

In other words, after occurrences of e_a at t there is a time window $[t + d_1, t + d_2]$ within which significantly more often than chance expectation there is at least one

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occurrence of e_b. The zero-hypothesis is that s_a and s_b are independently distributed and that s_b has constant probability = N_b/T of occurrence per unit time throughout [1, T]. (Note that event-types are considered as a patterns of length m=1.) For examples of t-patterns, respectively, $X_1...X_{27}$ and $X_1...X_9$, with their imposed binary trees see the left sides of figures 3 and 4.

6.2.3 The detection algorithm

The detection algorithm searches for all possible critical interval relationships between all the initial series in the data as well as those created for the patterns found during the detection process and added to the data.

Each time a critical interval is found between A and B (whether event-types or patterns) all those instances of A and B where B begins within the critical interval measured from the last element of A are connected to form an instance of pattern (A B). If A and B are of lengths m_1 and m_2, respectively, the resulting pattern (A B) will be of length $m_1 + m_2$ and its instances will start the first element of A and end at the last element of B. (An event-type can be see as a pattern of length m = 1 and therefore as its own first and last element.) As many different significant binary trees may correspond to the same underlying t-pattern, this algorithm alone frequently makes many equivalent as well as partial (i.e., with missing elements) detections of the same underlying pattern which often leads to combinatorial explosions and results impossible to digest.

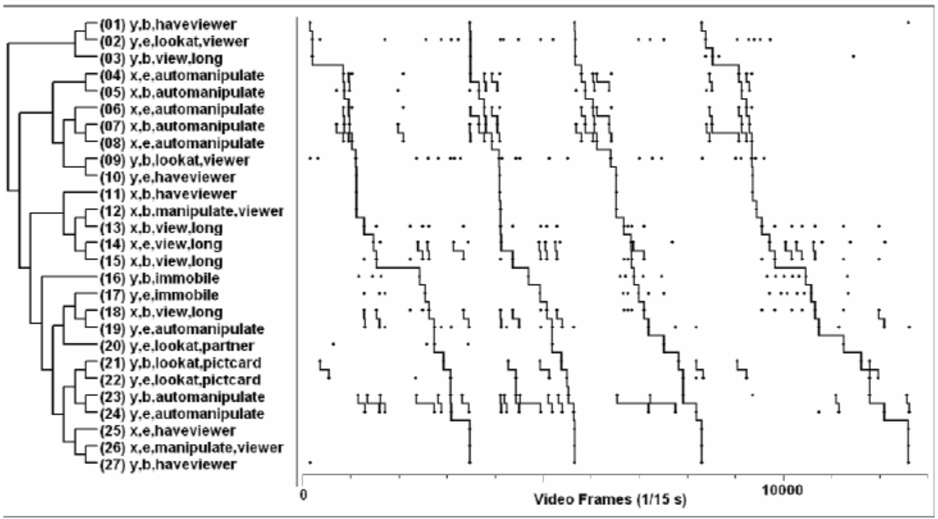

Figure 3. This figure shows the longest pattern m=27 detected in *Data1*. On the left is the terminal string of event-types: $X_1 \ldots X_{27}$ as well as the binary tree of critical interval relationships. On the right of each event-type its occurrence time series is shown. Connecting lines show how points from each series are connected to form the pattern that occurs four times and in this case begins and ends with the same series which therefore appears twice (that is, $X_1 = X_{27}$). The four occurrences of this single pattern cover 100% of the observation period of approximately 13.5 min. P(template) < 10^{-25}, P(4 template occurrences) < 10^{-102}. Longest pattern length after 1000 rotations was m=12 while the number of occurrences of patterns of that length was 107.16 standard deviations greater than random mean. See text.

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By assuming the underlying t-patterns and comparing all patterns that are detected, a kind of completeness competition is thus set up between detected patterns such that only and most complete survives.

6.3 Searching for more structure

Looking at figures such as those above and just thinking about every-day behavior and interactions, it is obvious that multiple (countless) aspects of the temporal structure of behavior are not treated by the t-pattern type. In trying to discover further structure, some new terms, definitions and algorithms have recently been added to the t-system and are described here in essence.

The following sections deal with issues concerning aspects hitherto ignored in the t-system. Amongst these are familiar phenomena such as bursts and cycles including related phenomena referred to as "t-blocks", "t-metronomes" and "ghost cycles" ("t-gcycles"). To keep the t-system as simple as possible and to facilitate the development of corresponding algorithms, all definitions of these phenomena are based on the critical interval relationship.

A newly developed approach will also be described for assigning a priori probabilities to whole patterns without consideration of the arbitrary binary tree structure used for their detection. To deal with the critical issue of statistical validation a new randomization method, called (random) rotation, is also described.

6.3.1 Bursts

One of the terms that now have been given definitions specially adapted to the t-system is the burst, referring to a number of points (events of the same type) occurring in succession with distances between them that are much shorter than the average. Until very recently, the t-pattern detection algorithms have not dealt directly with such phenomena which have consequently been invisible to the corresponding software. But now a "t-burst" is defined and detected as a special kind of t-pattern and can therefore also occur as a component of more complex t-patterns (including higher-order bursts). Any t-pattern can also form t-bursts, which in turn may occur as components of more complex t-patterns.

The t-burst is defined and integrated into t-pattern detection on the basis of the critical interval relationship requiring minimal changes to the existing algorithms. The t-burst thus exists in a single series of n points, t_i ; i=1,2,..n, within [1, T] if a fast critical interval, [1, d] exists between the two sub-series t_i ; i = 1, 2, n-1 and t_i where i = 2, 3,..n and these bursts occur where consecutive points in t_i are separated by distances within the critical interval range; that is, where $t_i + 1 <= t_{i+1} <= t_i + d$. Since the series t_i may represent either an event-type (A) or a pattern (Q), patterns such as (A A) and (Q Q) may be formed and become components of higher order t-patterns. See, for example, the burst X_4 and X_5 in event-type "n,b,fou,tac" (novice begins providing information) in figure 4. A more unusual example can be seen in figure 5, the pattern $X_1...X_{12}$ which is a single burst of three occurrences of the pattern $X_1...X_6$ or $X_7...X_{12}$. This also shows that the detection of a burst that only occurs once is possible). Both figures are based on data from a previously published study of children's problem solving interactions [13].

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6.3.2 Blocks

Some t-patterns have a strikingly similar duration each time they occur. This is most apparent when the patterns are long, including many critical intervals allowing for considerable variation in the total duration of different instances, that is, the time from X_1 to X_m.

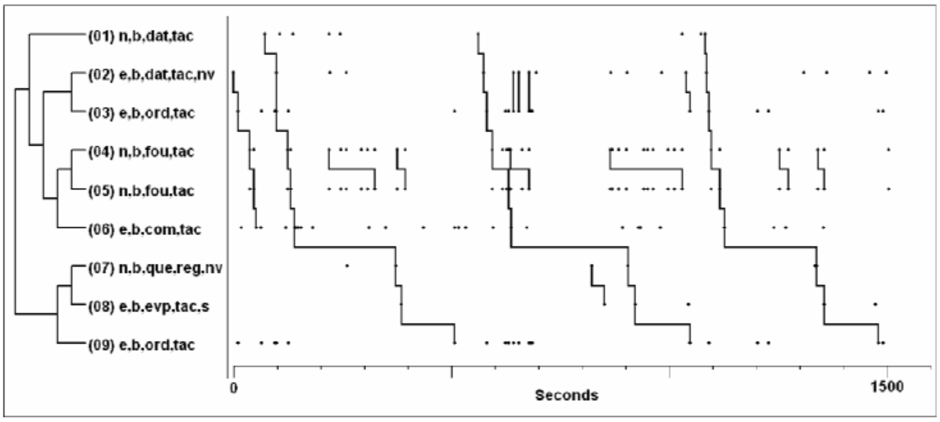

Figure 4. This figure shows a highly significant pattern detected in children's approximately 25-min puzzle-solving dyadic interaction. P(template) < 10^{-6} and P(3 template occurrences) < 10^{-18}. Maximum length after 1000 random rotations was m=7 with occurrence in the real data >26 standard deviations over random mean. It contains a burst in n,b,fou,tac, which is therefore shown twice; as X_4 and X_5 forming the first level pattern (X_4 X_5) sometimes occurring as parts of the larger pattern $X_1..X_9$. Actors are e and n. Only the beginnings of behaviors, "b", were coded. Temporal resolution = one second. Dat = directs the other's attention. Tac = task (solving a puzzle). "nv" = nonverbally; "ord" = gives and order; "que" = asks a question; "reg" = rule for the solution of the puzzle; "evp" = positive evaluation of progress (in solving puzzle); "com" = makes a comment; "s" = soliloquy (talking to oneself); "fou" = provides information. N,b,fou,tac thus means: n begins providing information regarding the task. Data from an earlier study [13].

To allow automatic detection and selection of such patterns they have been given a simple formal definition and named "t-blocks". A t-block is thus defined as a t-pattern where there is a critical interval relationship between its beginning and end elements, X_1 and X_m. For example, a repeated pattern ABCD is a t-block if there is a critical interval relation between the occurrences series of, respectively, A and D, when these occur as parts of ABCD. All first level patterns, having only two event-types related by a critical interval, are thus t-blocks by definition. The pattern $X_1..X_9$ in Figure 4 is an example of a t-block.

6.3.3 Cycles

A cyclical occurrence of event-types and t-patterns is frequently observed in interactions (see for example, Figures 3 and 4), but cyclical aspects are not involved in the definition of t-patterns, and the corresponding detection algorithms do not deal with them. The following definition of cyclical occurrence based on the critical interval relationship now allows consideration of this aspect for event-types as well as t-patterns. The definition is partly inspired by literature regarding (approximate translation) symmetry cited above. For a single series, the definition of cyclical

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occurrence is identical to that of bursts, except that the fast critical interval [1, d] is replaced by a *free* critical interval [d_1, d_2] (where both the lower and the upper limit may vary). A pattern, Q, is by definition cyclical if at least one of its terms, $X_1 \ldots X_m$ (when occurring as such) is cyclical (and is therefore called a cyclical term in Q).
A pattern is said to be x% cyclical if x% of its terminals are cyclical in this way. Differing from bursts, no connection operation is at the moment used for this relationship. Patterns are thus classified as cyclical or not, but no new entities and occurrence series are formed.

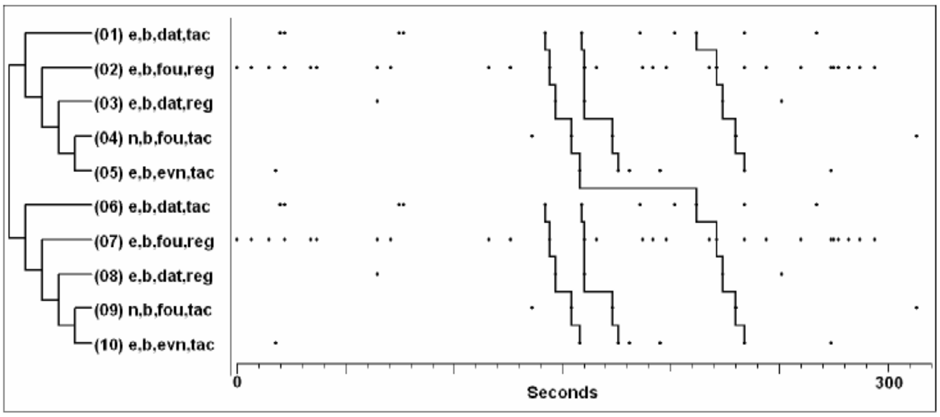

Figure 5. This figure shows a pattern of length m=10 that is a single burst of three occurrences of a t-pattern of length m=5: $X_1 \ldots X_5$ (or $X_6 \ldots X_{10}$). P(template) = P(1 template occurrence) < 10^{-6}; as the burst only occurs once. Occurrence deviation from random mean after 1000 rotations = 3.8 standard deviations. The binary detection tree is on the left side and the occurrence series of each event-type appears immediately to its right. Connection lines show how the three occurrences of pattern are constructed. For burst patterns, the pattern is shown twice as, respectively, $X_1 ... X_5$ and $X_6 ... X_{10}$. A horizontal line connects the ending (X_5) of the first instance and the beginning (X_6) of the last instance of in the burst; here of the first and third instances of pattern $X_1 \ldots X_5$ (or $X_6 \ldots X_{10}$). Evn = negative evaluation (of progress in solving the puzzle). See text and figure 4 regarding the meaning of the other codes. Data from an earlier study [13].

6.3.4 Metronomes

When looking at a t-pattern diagram, for example, Figures 3 and 4, not only might the cyclical occurrence of a pattern be striking, but also some of its terms considered *per se* (as independent event-types) may also seem cyclical with a similar periodicity and to act as a kind of metronome for the pattern. This is most striking when such event-types occur as the first element of a pattern and seem to direct or guide the cyclical rhythm of the full pattern (as, for example, in Figure 3). But as defined here, such "t-metronomes" may also happen at any position other than the first within $X_1 \ldots X_m$. Moreover, some such t-metronomes may occur in a cyclical fashion while the pattern, within which it is a cyclical term occurs more rarely, i.e. using a musical reference, the pattern may happen only on some of the metronome's beats. Per definition, a t-metronome is a cyclical terminal of a pattern with critical interval [d_1, d_2] which, when considered as an event-type independently of the pattern, it is also cyclical with a critical interval [xd_1, xd_2] such that there is an overlap between [k * xd_1, k * xd_2] and [d_1, d_2]; where k is a positive integer. A number of such metronome event-types have just been detected and will be reported later.

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6.3.5 Cyclical patterns without a metronome

Cyclical patterns that do not have any metronome components are here called (for want of a better name) "ghost cycles" (t-gcycles) as they behave cyclically without any visible guidance. Such patterns are now routinely found and illustrate as earlier suggested that prior detection of patterns can be necessary for the discovery of cyclical organization, that is, when such organization is not present in any of the initial data series (14).

6.4 Templates and a priori probabilities

It is mainly for practical reasons that t-patterns are defined and detected as binary tree structures as the testing of all possible fairly long t-patterns would otherwise not be feasible even for the fastest computers. However, when a t-pattern has been detected, it is possible to ignore the tree structure and simply look at the pattern as under II) above and try to assign an a priori probability irrespective to any tree structure:

$X_1 \, [d_1, d_2]_1 \, X_2 \, [d_1, d_2]_2 \, X_3 \ldots X_i \, [d_1, d_2]_i \, X_{i+1} \ldots X_{m-1} \, [d_1, d_2]_{m-1} \, X_m$

And in the fully specified case of a detected pattern, for example, as:

$A \, [3, 15]_1 \, B \, [17, 39]_2 \, C \, [5, 12]_3 \, D$

Where A, B, C, and D are particular event-types.

This kind of structure derived from a t-pattern is here referred to as a t-template, W.

It can also be expressed exclusively in terms of the lengths of the intervals:

$A \, [13]_1 \, B \, [23]_2 \, C \, [8]_3 \, D$

As simple estimate of the probability of finding a single match for such a structure in a shuffled version of data will here be used as an estimate of the a priori probability of the template. For the above template this a priori probability P(W) is defined as the product P(of finding a B within a randomly placed interval of length 13) * P(of finding a C within a randomly placed interval of length 23) * P(of finding a D within a randomly placed interval of length 8). Any detected t-pattern can thus be assigned a probability equal to that of its implicit t-template, which also may be of other important use (see below).

Thus if a pattern Q with t-template W is detected, for example, n times in real data, D, the a priori probability assigned to this is thus $P(W)^n$, which is also called the a priori probability of Q's occurrence in D. These probabilities are often extremely small so they are best expressed as logarithms (here, base 10, i.e., log10) and values between 10 and 200 are often seen. This is actually in good accordance with the extreme significance of differences between the numbers of detected patterns of each length in, respectively, real and randomized data, where frequently $p < 10^{-7}$ (approximately) for all but the shortest patterns (see below).

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The computation of the p values for such deviation was done with Theme 6 beta version. At the time of this writing it uses the “NormDist” function in TurboPower’s Systools for Delphi, which returns zero for values lower than approximately 10^{-7}, which happens not far from five or six standard deviations. For this reason p values are not presented for real versus randomized data comparisons below, but in terms of standard deviations that typically far exceed that number. (The NormDist routine is to be replaced in Theme by a more powerful routine.)

6.4.1 Statistical significance, shuffling and random rotation

The detection of critical intervals and therefore t-patterns is based a zero hypothesis that is tested possibly millions of times when exploring for patterns in a single data set. Obviously, many would thus be significant even if the data were random. A crucial issue here is thus whether findings are statistically significant, that is, whether much fewer patterns are detected after randomization of the data.

Already in the first version of THEME™ ([15, 16]; (copyright and development by PatternVision, www.patternvision.com; distributed by Noldus Information Technology, www.noldus.com), this issue was tackled quite directly as each search in real data was followed by a search in a shuffled version of the same data, that is, after the time points in each series in the real data have been randomly redistributed over the observation period. In this way the size of the data remains the same as the number of series, and the number of points in each, remain unchanged. By repeatedly shuffling and then searching for patterns in the same data set, an occurrence distribution with a mean and a standard deviation is obtained for each pattern length. This allows comparison with the findings in the original (un-shuffled) data and differences can be expressed in terms of standard deviations and p values.

For most data, these differences have been considerable, for example, between 5 and 20 standard deviations with corresponding (extremely) low p values, and as expected the differences are generally much greater for the longer patterns. For the longest patterns detected in real data, typically none at all are found after shuffling the data and even after repeating the randomization and search process more than a thousand times, which is, for example, the case for the patterns in figures 3 and 4. It is interesting that for the shortest patterns there may actually be no difference at all or it may even occasionally be negative, that is, slightly more very short patterns may be found in the randomized data. This could easily be the case if, for example, many of the coded event-types are of a kind that do not occur in t-patterns, except in randomized (non-sense) data.

6.4.1.1 Deciding significance for “synfire” patterns and t-patterns

With regard to the detection of so called “synfire” patterns in neuronal activity (see, for example, 17, and references therein) the possibility has been raised that shuffling data may give misleading results, exaggerating the difference between random and real data. Synfire patterns have some similarity with t-patterns and may in essence be described as t-patterns where all critical intervals are the same and very narrow, for example, [0, 1] or [1, 1]. The detection algorithm therefore does not detect critical intervals relationships, but tries to find matches for the prefixed one (which remains unchanged throughout). No completeness competition between patterns is involved either.

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The number of synfire patterns detected in real data compared to shuffled data is small and may not be significant and the possibility exists that the differences do not reflect dependencies between series in the real data, but rather the particular structure of each of the series. Different from the synfire patterns, the differences between the number of t-patterns detected in real and shuffled data is typically great or somewhere between 5 and 200 standard deviations. However, a new randomization method has been developed that maintains practically unchanged the structure of each series while randomizing the relationship between them. This can be visualized as figure 1 being wrapped around a cylinder whereby each series forms, around the cylinder, a circle that can be rotated by a random number of degrees independently of the others. Thus, instead of shuffling every series, all series are left unchanged, but each one is rotated by a new random number of degrees (between 1 and 359).

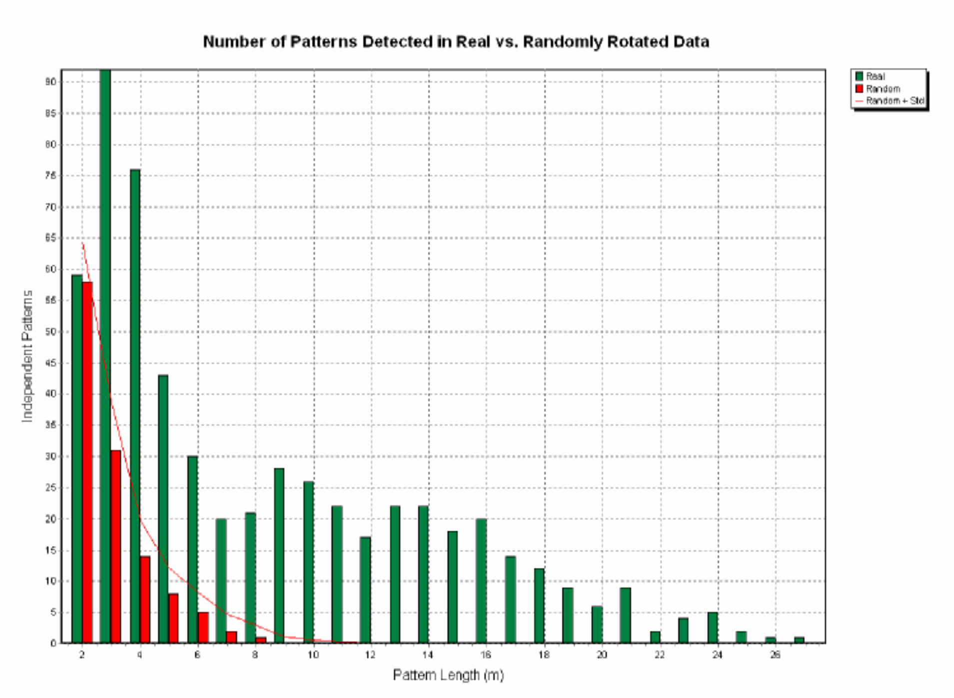

Figure 6. This figure shows for *Data1* the number of patterns of each length detected in the initial (real) dataset as well as the mean number for each length detected in one thousand searches in the same number of randomly rotated (see text) versions of the same data. The line shows mean + 1 standard deviation for the 1000 random cases. Note that no patterns of length greater than 12 are detected in any of the randomized data, while patterns of length up to 27 are detected in the real data. (See also corresponding Figures 7 and 8.)

Since much more of the initial structure of the data is thus maintained than in the shuffle case, differences between randomized and real data are also smaller for rotated than for shuffled data. However, since the differences are generally much greater than usually required in significance testing, the differences between the two methods have not yet been important enough to change conclusions.

Both kinds of test have now been implemented in the Theme software (version 6) allowing easy comparison of the results. Using *Data1* (Figure 1), Figures 7 and 8,

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show results for, respectively, the shuffling and rotation test obtained through one thousand repetitions of randomization followed by detection for each type of test. Note that patterns longer than m=12 are not found in either kind of randomized data, while in the real data patterns up to length 27 are detected. For both types of randomization the differences obtained are extreme so finding the associated p value is usually impossible due to the above mentioned limitation in the currently used subroutine which returns $p < 10^{-7}$ as zero. Figure 8 only concerns cyclical patterns. For cyclical patterns in neuronal data, Figure 9 shows differences between real and random data using the rotation test (with one thousand repetitions). In this case due to over abundance of patterns, the analysis was limited to only two hierarchical patterns levels (i.e. in the binary pattern tree) so the longest patterns are of length m=4. The difference between random and real in this case began at 81 standard deviation for m=2 and went up to 240 standard deviations for m=4.

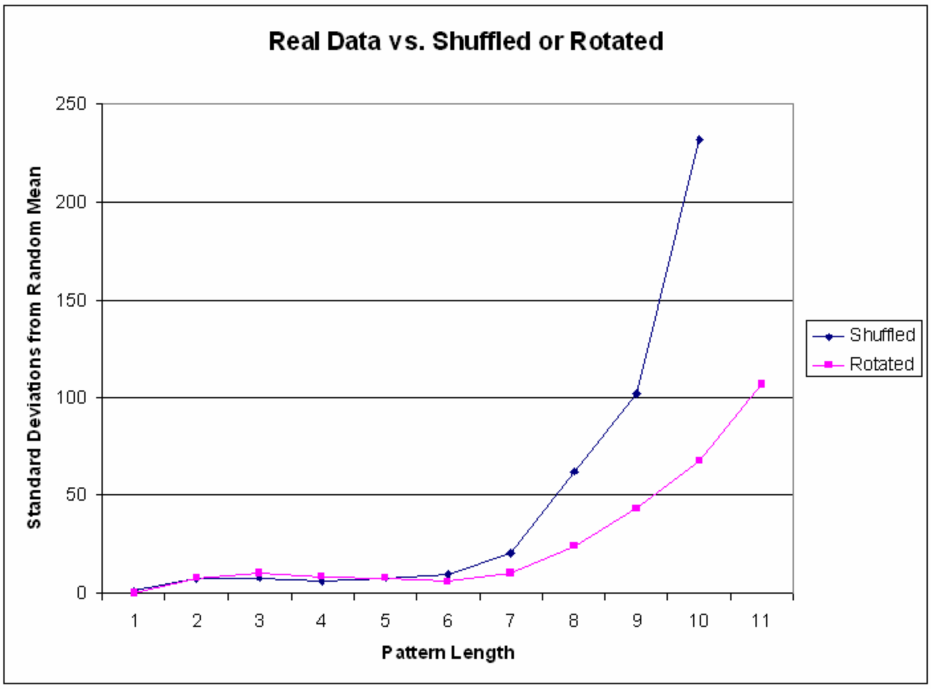

Figure 7. This figure shows the difference between number of patterns detected in real data, *Data1*, versus the average found over 1000 repetitions of, respectively, rotation and shuffling of that data. It can be seen that from about length 7 the deviation increases much faster with increasing pattern length in the shuffling case. No patterns of greater length were found in the randomized data, while patterns up to length 27 were detected in the initial *Data1*.

In general, the more inherent structural characteristics of behavior are considered, the greater the difference should be between results obtained from, respectively, real and randomized data (whether shuffled or rotated). In this respect the importance of the cyclical aspect is clearly indicated regarding the Data1 (Figure 1) since considering cyclical t-patterns only, the difference between real and randomized data increases considerably as may be seen by comparing figures 7 and 8. This has also been found

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in all other data hitherto analyzed including interactions in a population of neurons as exemplified in Figure 9. Figure 6 shows differences in pattern detection between real and rotated versions of *Data1* (shown in Figure 1).

6.5 Conclusions

Considering the above results of randomization, both shuffling and rotation, it seems that assignment of a priori probabilities to t-patterns (t-templates) in the way suggested above may be reasonable and that the arbitrary tree structure may be safely disregarded after detection. However, a new algorithm has been developed that successfully matches t-templates, without consideration of the tree structure, in the data set where they were detected while respecting the order and mutual exclusiveness of pattern occurrences and generating the same series of terminal occurrence times.

In terms of t-patterns, interactions between humans as well as neurons appear to be highly structured.

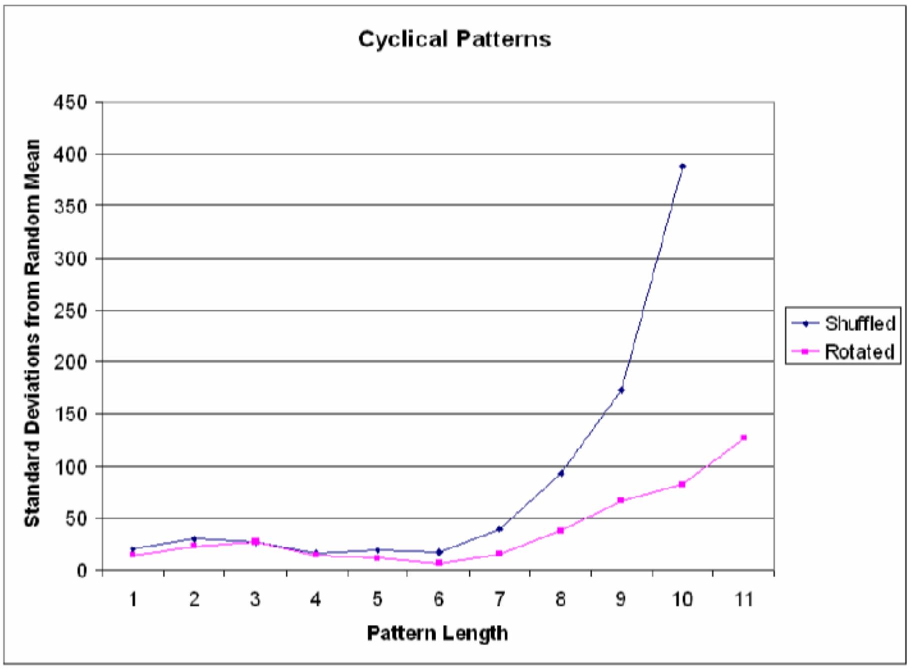

Figure 8. This figure only concerns cyclical patterns. It compares results obtained with the two different methods of randomization, shuffling and rotation, using *Data1*. It can be seen that from about length 7 the deviation increases much faster with increasing pattern length in the shuffling case. It also shows that the deviation is quite extreme in both cases. No patterns of greater length were found in the randomized data, while patterns up to length 27 were detected in the initial *Data1*.

But some questions arise. Are t-patterns equally relevant in the temporal organization of neuronal and human interactions? Are both organized according to a common principle somehow related to the t-pattern structure? What is that principle? Are the t-patterns seen in human interactions higher-level reflections of such underlying

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structure and, if so, how deep down in nature's organizational ladders might such structure be found?

"Human biology is anchored in concrete anatomy and genetics, providing fundamental elements from which to draw interconnections and with which to construct theory. The social world, in contrast, is a complex set of abstractions representing the actions and influences of the relationships among individuals, groups, societies, and cultures. The differences in levels of analysis have resulted in distinct histories, research traditions, and technical demands, leaving what some regard as an impassable abyss between social and biological approaches. The assumptions in social neuroscience, in contrast, are that the abyss can and must be bridged, that the mechanisms underlying mind and behavior will not be fully explicable by a biological or a social approach alone, that a multi-level integrative analysis may be required, and that a common scientific language – grounded in the structure and function of the brain and biology – can contribute to this goal." ([18], p. 5).

Such unity of language, however, is currently hardly favored by the often confusing use of the term "biological". For example, probably every biologist would consider social insect hives with all their social organization and interactions as biological, while hundreds of thousands of human hives (villages, towns and cities) with their however varied social structures, some ancient and others new, are typically not considered biological. Some biologists even appear to have a kind of dualistic view of human social phenomena including what often is referred to with limited clarity of definition as "culture". Moreover, the molecular view of life [19] is clearly dominant in modern biology and some biologists, at least in informal discussions hardly seem to view Darwin himself as a biologist. Rather amazing analogies in terms of structure and function of repeateded patterns actually seem to exist between information molecules and human cultural phenomena and even in terms of t-patterns [12].

All of science deals with the discovery of nature's recurrent patterns across time and/or space and much of the complex set of social abstractions mentioned above mostly seems to refer to (classes) of repeated interaction patterns of such general importance that they have been given names by systems of interacting humans. Clearly, the behavioral phenomena they refer to are no less observable or objective than those of, for example, physics and chemistry.

Like the behavioral and social sciences, molecular biology and genetics are about patterns and also depend on the truly common and ever expanding language of science, from chemistry to astronomy, "the science of patterns", mathematics, which has experienced such explosive growth and specialization in the 20th century. This special language, however, focuses less on the size and kind of elements, whether they be quarks, phonemes, molecules, texts, cells, or humans, but more on the joy of discovering unity of structure across different phenomena and scales. And possibly the study of interaction and communication still needs its own new mathematics to be developed.

The above results suggest that even toddlers playing freely with a toy for a few minutes quickly organize their time, the temporal structure of their interaction, in a surprisingly rigid and repetitive way, that is, showing striking translation symmetry. Other aspects of symmetry regarding t-pattern detection have been considered elsewhere [20]. Also surprising is that an adult watching the interaction is not aware

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of or is unable to detect but a minimum of the regularity that is developing in front of his/her eyes. All this calls to mind classical questions of nature versus nurture as, for example, in this paragraph from [21, p. 4]:

"A cross-specific comparison of courtship rituals highlights the fundamental distinction between naturally based and socially based sequential rigidity, and serves to demonstrate where nature ends and social convention begins. The courtship ceremonies of water salamanders or sticklebacks, for example, generally consist of biologically determined "reaction chains" wherein each link in the chain functions as a necessary "releaser" of the mate's next move. Ritualized fanning by the male, for instance, is indispensable for "releasing" the female's entrance to the nest and must, therefore, precede it." {Emphasis added.}

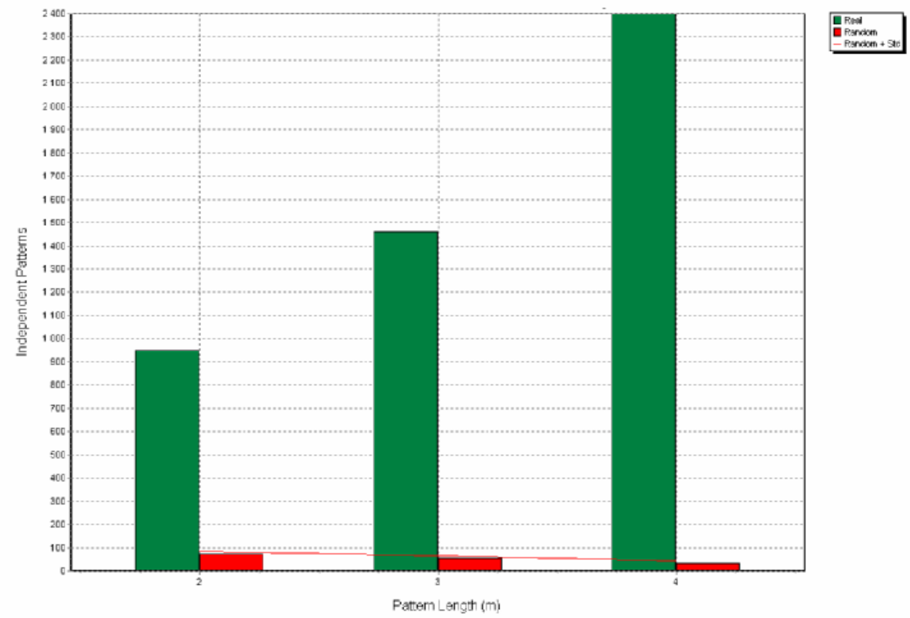

Figure 9. This figure shows the number of cyclical t-patterns detected in neuronal interaction data and the mean number detected in one thousand random rotations of the same data. The data used are form an ongoing study [7].

But at another level it may truly be in the *nature* of interacting humans, even quite unconsciously, to improvise patterns and then repeat them approximately unchanged as in so many other cases of nature's approximate translation symmetries. The meaning of it all may also be more or less unconsciously perceived. And while some such patterns may be short-lived others survive, that is, become more common for some time, much as in other evolutionary processes, which humans also used to be unaware of. The conventional structure of rituals, ceremonies and other more or less rigid routines of social existence, may thus in each case be more or less arbitrary, but the fact that they are there, that they are created and repeated by interacting humans,

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may still be a reflection of deep human tendencies and possibly with roots in nature's most general spatio-temporal symmetries.

It is hoped that t-pattern detection may be of help in dealing with issues of intention, meaning, and mistakes in communication and steps have already been taken in that direction [22]. In the context of communication, questions also clearly arise regarding how much of the patterning is semi-conscious, conscious, intentional and/or communicative? Furthermore, what communicative effects can be expected when such symmetries are broken?

6.6 Appendix

The following is a short list of the meanings of some of the terms that appear in Figures 1 to 3. The children are using a special viewer to look at picture-cards (pictcard). There is only one viewer. X and Y are the two actors; b and e indicate whether the behavior described is beginning or ending; Automanipulate = the actor touches any part of own body; immobile = the actor does not move any body part and is like frozen; order = verbally orders the other to give up the viewer; long = more than 3 seconds; short = less than 3 seconds. For example, x,e,walk means x ends walking.

The following list shows the the label of each event-type with its number as on the Y-axis in figure 1: **1** x,b,automanipulate; **2** x,b,glanceat,partner; **3** x,b,glanceat,pictcard; **4** x,b,glanceat,viewer; **5** x,b,haveviewer; **6** x,b,immobile; **7** x,b,kneel; **8** x,b,laugh; **9** x,b,lie; **10** x,b,lookat,partner; **11** x,b,lookat,pictcard; **12** x,b,lookat,viewer; **13** x,b,manipulate,viewer; **14** x,b,order,viewer; **15** x,b,pull; **16** x,b,sit; **17** x,b,stand; **18** x,b,view,long; **19** x,b,view,short; **20** x,b,walk; **2**1 x,e,automanipulate; **22** x,e,glanceat,partner; **23** x,e,glanceat,pictcard; **24** x,e,glanceat,viewer; **25** x,e,haveviewer; **26** x,e,immobile; **27** x,e,kneel; **28** x,e,laugh; **29** x,e,lie; **30** x,e,lookat,partner; **31** x,e,lookat,pictcard; **32** x,e,lookat,viewer; **33** x,e,manipulate,viewer; **34** x,e,pull; **35** x,e,sit; **36** x,e,stand; **37** x,e,view,long; **38** x,e,view,short; **39** x,e,walk; **40** y,b,automanipulate; **41** y,b,crawl; **42** y,b,glanceat,partner; **43** y,b,glanceat,pictcard; **44** y,b,glanceat,viewer; **45** y,b,haveviewer; **46** y,b,headtilt; **47** y,b,immobile; **48** y,b,kneel; **49** y,b,laugh; **50** y,b,lie; **51** y,b,lookat,partner; **52** y,b,lookat,pictcard; **53** y,b,lookat,viewer; **54** y,b,manipulate,nose; **55** y,b,manipulate,viewer; **56** y,b,order,viewer; **57** y,b,sit; **58** y,b,stand; **59** y,b,view,long; **60** y,b,view,short; **61** y,b,walk; **62** y,e,automanipulate; **63** y,e,crawl; **64** y,e,glanceat,partner; **65** y,e,glanceat,pictcard; **66** y,e,glanceat,viewer; **67** y,e,haveviewer; **68** y,e,headtilt; **69** y,e,immobile; **70** y,e,kneel; **71** y,e,laugh; **72** y,e,lie; **73** y,e,lookat,partner; **74** y,e,lookat,pictcard; **75** y,e,lookat,viewer; **76** y,e,manipulate,nose; **77** y,e,manipulate,viewer; **78** y,e,sit; **79** y,e,stand; **80** y,e,view,long; **81** y,e,view,short; **82** y,e,walk.

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