How Long Is the Coastline of Teamwork?

A Neurodynamic Model for Group and Team Operation and Evolution

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Abstract. A five-state Markov model is proposed for group and team operation and evolution that has a stronger basis in neurodynamics, greater descriptive accuracy and higher predictive value than many existing models. The derivation of this model from the symbolic analysis of normalized EEG activity during assigned team and group tasks is discussed, as are observations on team and group dynamics which emerge from the model. The predictive value of the model is shown when applied to independent data from submarine crew evolutions. Observations are offered on team dynamics which show the five-state model and its accompanying state transitions to be necessary and sufficient to describe both linear and non-linear team dynamics, and to begin unifying these traditional and new approaches in a straightforward way.

Keywords: nonlinear dynamics, neurodynamics teamwork, markov model, state transition, EEG symbol, tuckman.

1 Introduction

Ever since Benoit Mandelbrot [1] observed in his 1967 paper *How Long is the Coast of Britain?* that the apparent structure of complex dynamical phenomena can depend on the scale of magnification used, students of group and team dynamics have struggled to find the right observational lens through which the linear and non-linear dynamics of teams and organizations can be understood equally well. With a large observational aperture, gestalt states applying to a whole work team – for example the "forming, storming, norming, performing, adjourning" states well-known from Tuckman [2] – make excellent sense and are well understood. At small apertures drilling down toward individuals, non-linear states and behaviors where there is important fine structure and no useful gestalt characterization make equally good sense and are partly understood, albeit much less predictably in outcome.

The difficulty to date has been that team and group dynamics from a standpoint of workplace productivity are often best viewed through apertures of medium size. At these

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apertures, traditionally-understood linear phenomena and more-recently investigated non-linear phenomena become equally important and can each be crucial in determining practical productivity outcomes. A straightforward model of team and group dynamics and evolution which unifies both linear and non-linear phenomena is therefore an essential tool for the modern practical leader.

It is also desirable to base any such model, where possible, on verifiable and observable facts about human cognition. Inference drawn from behavior is important and remains the basis of much of psychology, but where it is possible to observe cognitive truth directly and thus to improve both the quality of observations and the insightfulness of descriptive models, opportunity exists for better science. Previously Stevens and colleagues [3] have taken advantage of technological developments in neuroscience and EEG monitoring to describe the neurodynamics of teams. This study extends these descriptions through the development of a five-state Markov model of teamwork which coalesces the complex phenomena into a simpler taxonomy that is well suited to practical team dynamics in industry and government.

2 Methods

2.1 Task and Teams

The custom-designed group task involved the team-based steering of a radio-controlled vehicle over an obstacle course and has been used for large-scale team training since 1996. The intention of the exercise was to present subjects with a significantly non-linear task to manage that kept the team motivated and engaged.

The operating area consisted of a Subject Zone within which subjects and experimenters were seated, and a Chicane Zone within which a radio-controlled vehicle, a varying number of chicanes, and four targets were located (Fig. 1). The Subject Zone contained seating for four subjects, each within easy reach of an individual controller for the vehicle steering system. Also within this area were a radio control system for the vehicle, a radiotelemetry monitoring and recording center for the subjects' EEG units, and a video camera to record video and audio. The Chicane Zone contained a small radio-controlled vehicle, four clearly-marked targets for the vehicle to strike, and a varying number and placement of wooden chicanes which was adjusted between the first and second task evolution. The targets each contained a detection system which caused them to emit clear visible and auditory feedback when struck and "set off" by the radio-controlled vehicle. Subjects were instructed that the goal was to use the vehicle to strike and "set off" all four targets in any order.

The radio-controlled vehicle operated like a tracked vehicle with steerage by wheels only. Ordinarily it would be a simple matter for a single operator to control this vehicle with a single radio remote, but the remote was replaced with a custom-built system which required four subjects to issue finely-coordinated commands in order to control the vehicle. Each subject was provided with a controller unit offering four buttons - left forward, right forward, left reverse and right reverse. Each function would only operate the vehicle as commanded if all four subjects pressed the relevant button at the same time; moreover each function would not cease to operate until all four subjects released the relevant button at the same time.

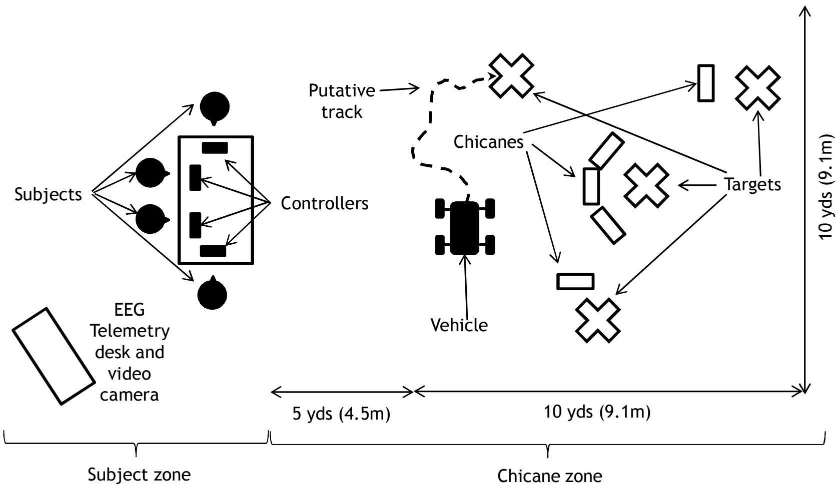

Fig. 1. Experimental layout for both task evolutions (chicane layouts vary)

The net effect of this system was twofold. Firstly, a high and constant level of engagement was required by the tight communication and feedback-management constraints of the task. Secondly, even with excellent team operation, a combination of mechanical tolerances, reaction time differences and uneven ground in the Chicane Zone meant that simple linear plans - such as the vehicle traveling in a straight line when appropriately commanded by the team – only worked for periods of a second or two. The combined effect yielded a non-trivial task in which linear and non-linear elements were combined in a way that could not be practically deconstructed.

Two task evolutions were performed that were characterized as “easy” and “hard”, with the “easy” evolution run first. In the “easy” evolution, only one or two chicanes were used, and none were placed in particularly awkward places with respect to the targets. In the “hard” evolution, targets were placed in more challenging locations within the Chicane Zone and more chicanes were used, some with awkward placing.

Subjects were also instructed to appoint a leader, and leadership was rotated after each target was “set off”, resulting in each subject being designated as the leader once per evolution, always in the same order.

The four subjects were tertiary-educated adults employed in the workforce by a range of employers, and not normally working together as a team. The same subjects were used for each task evolution, located in the same four physical positions, and with subject order preserved in the symbol elements generated for both. Subjects (n=4) performed the two task evolutions with a break in between. During each evolution of the task, all four subjects were simultaneously monitored by EEG.

2.2 Electroencephalography (EEG)

The B-Alert® system by Advanced Brain Monitoring, Inc. is an easily-applied wireless EEG system that includes software that identifies and eliminates multiple sources of biological and environmental contamination and allows second – by -second classification of cognitive state changes [3]. The 9-channel wireless headset includes sensor site locations: F3, F4, C3, C4, P3, P4, Fz, Cz, POz in a monopolar configuration referenced to linked mastoids. B-Alert® software acquires the data and quantifies engagement (EEG-E) in real-time.

For each task the four team members were rank ordered (4 = highest, 1 = lowest) with regard to the levels of EEG-E. The positions of the leaders in each performance were then compared with the average positions of the remaining team members. In all eight performances the leader had the highest or second highest levels of EEG-E (mean ranking Leaders = 3.34, Other Members = 2.21, $T = 4.80$, $df = 7$, $p < 0.002$).

3 Design and Procedure

3.1 Team Neurodynamics

For neurodynamics modeling, normalized second-by-second values of EEG-E were concatenated into vectors representing the levels being expressed by each team member. For instance, in Fig.2A team members 3 and 4 were expressing below average levels of EEG-E and would be assigned values of -1. Team members 1 and 2 were expressing above average levels of EEG-E and were assigned the value 3. A team member with average levels would be assigned the value 1; the vector representation was therefore (3, 3,-1,-1). Using unsupervised artificial neural networks (ANN) where the nodes were arranged in a linear configuration, the vectors from all performances were modeled into collective team variables that are termed neurodynamic symbols of engagement (NS_E). ANN classification of these second-by-second vectors created a symbolic state space showing the possible combinations of either EEG-E or EEG-WL across team members (Fig. 2A). One effect of the linear configuration of neural network nodes during ANN training is that symbols that resemble each other become closely aligned. For instance, in Fig. 2B NS 1-5 represented periods where most team members had average / below average levels of EEG-E while NS 20-25 represented times when most had above average EEG-E levels.

While a symbolic view of the state of the team is useful for characterizing team neurodynamics, it is not the best representation for quantifying team neurodynamics. Although there are methods for the quantitative representation of symbols, we chose a moving average window approach to derive numeric estimates of the Shannon entropy of the NS symbol stream [3]. Entropy is expressed in terms of bits; the maximum entropy for 25 randomly-distributed NS symbols would be log2 (25) or 4.64.

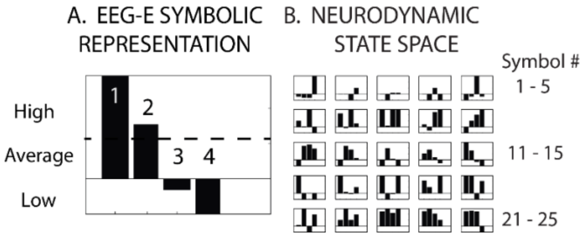

Fig. 2. Data Flow for Creating Team Neurodynamics Models. ANN classification of second-by-second vectors (A) creates a symbolic state space showing the possible combinations of EEG-E or EEG-WL across (numbered) members of the team (B).

For comparison, an entropy value of 3.60 would result if roughly half (12) of the NS symbols were randomly expressed. To develop an entropy profile over a session, the NS Shannon entropy was calculated at each epoch using a sliding window of the values from the prior 60 seconds. As teams entered and exited periods of organization, the entropy should fluctuate as a function of the number of NS symbols being expressed by the team during a block of time [3]. As shown in Fig. 3 for the hard problems, there were significant entropy fluxes, with the periods of greatest team organization (i.e. the lowest NS_E entropy) occurring around periods where there was a target hit, or an expected target hit.

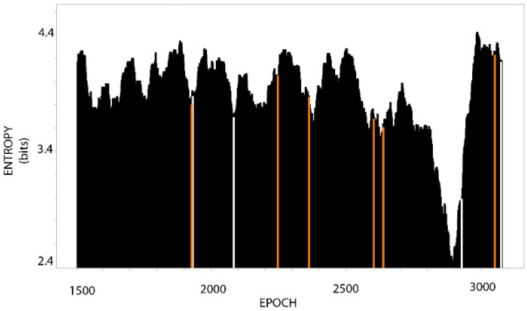

Fig. 3. NS_E Entropy Fluctuations. The fluctuations in the NS_E entropy levels are shown for the hard problems. The lines mark where there was a hit, or a near miss.

3.2 Symbols and Phase Transitions

One way of visualizing the short-term structural dynamics of a data stream is to create transition maps that plot symbol being expressed a time t vs. that at time $t + 1$; such maps are shown for the "easy" case (Fig. 4A) and "hard" case (Fig. 4B). An examination of the phase transition diagrams for the "easy" and "hard" cases reveals attractive basins along the diagonal in both cases, representing relatively stable symbols, and also off-diagonal attractors which indicate common symbol transitions. The hard problems showed fewer of the off-axis transitions indicating a more organized cognitive state. Randomizing the NS data stream destroyed this organization (Fig. 4C). As expected from the transition matrices, the harder tasks had lower overall NS_E entropy levels. These transitions show a practical landscape of team preferences in the context of the task environment. In the “easy” case, symbols of particular interest on the diagonal are 5, 7 and 25. High-usage off-diagonal symbol transitions include 15-to-25, 25-to-15, 23-to-7 and 27-to 7. It is also apparent that while some symbol transitions are bilaterally symmetrical, for example 15/25, not all are. In the “hard” case, symbols of interest include 1, possibly 11 and 19, and 21 along the diagonal; and the off-diagonal transition 1-to-21. Similar observations about possible bilateral asymmetry apply. The phase colorings also denote considerable additional structure showing relationships of interest between symbols, but these seem numerous, complex, and confusing as they stand.

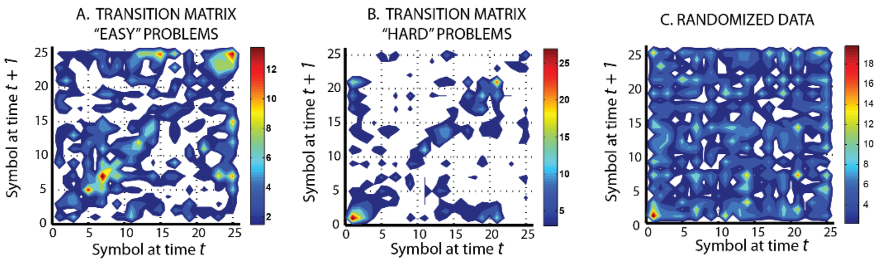

Fig. 4. Neurodynamic Symbol Transition Matrices for Easy (A) and Hard (B) Problems. Randomization of the combined data destroyed the structure (C).

The dimensionalities of the data streams were estimated by the Hurst exponent, where an exponent of 0.5 indicates a random process while an exponent between 0.5 and 1 indicates a persistent process, i.e. an upward or downward trend is likely to continue. The Hurst exponents for the data stream in Figures 4A and 4B were 0.88 and 0.67 respectively suggesting the NS data streams for these tasks have a fractal structure; i.e. a process somewhere between deterministic and random. As expected, randomizing the data stream reduced the Hurst exponent to 0.47.

4 Analysis

4.1 Development of a Symbol Taxonomy for Transitions

To extend the transition matrix representation, a taxonomy was applied to the major transitions in Fig. 4, focusing on the symbol transitions that were most heavily-used by the team while accomplishing both the “easy” and the “hard” tasks. The goal was to develop a taxonomy based on the distributions of EEG-E by different members of the team (Table 1); the motivation for this scheme was based on general principles from leadership development discussed later. The move from 25 EEG symbols to five underlying and descriptive and characterized states for the team – using the term “states” in the Markovian sense – is key, and the five Markov states (Dominant, Dyadic, Collegiate, Outlier, Dormant) are used subsequently. The outstanding questions, covered next, are how we can maximize the information yield of the data under this model, and whether the five states are necessary and sufficient.

Table 1. Taxonomy based on the distributions of EEG-E

Evolution	Symbol	Name	Characterization
Easy	5	Dominant	One person with high engagement; the rest follow with uniformly lower engagement.
Easy	7	Dyadic	One small clique with high engagement; the rest follow with uniformly lower engagement.
Easy	15	Outlier	One small clique with distinctively low engagement; the rest with much higher engagement.
Easy	23	Collegiate	Uniformly high and approximately equal engagement
Easy	25	Outlier	Ibid
Hard	1	Dominant	Ibid
Hard	11	Outlier	Ibid
Hard	21	Outlier	Ibid
All	2,3,4	Dormant	Uniformly low and approximately equal engagement

4.2 Data Aggregation

In both the easy and hard cases, 25x25 transition frequency matrices – the numerical, and accurate, counterpart of a colored phase transition diagram – were generated. Each symbol was assigned to a state in the taxonomy, and then the frequency transition counts for each state were aggregated. The resulting state transition tables were:

Table 2. Aggregated transition counts,"easy" case, row-column order

	COL	DOM	DOR	DYA	OUT
COL	57	34	9	46	60
DOM	22	91	31	85	94
DOR	11	44	28	29	31
DYA	53	80	41	113	102
OUT	63	74	33	117	155

Table 3. Aggregated transition counts, "hard" case, row-column order

	COL	DOM	DOR	DYA	OUT
COL	23	18	2	30	28
DOM	20	127	66	118	99
DOR	7	81	60	39	44
DYA	24	123	53	140	86
OUT	27	81	50	99	125

Aggregating counts in this way allows us to use the theoretical maximum information rate from the available data. Moreover, as we apply the taxonomy in part 4.1 to all 25 symbols, we observe that this taxonomy is necessary and sufficient to cover all symbols. There are no symbols that do not "fit", but if any one of the five states is removed from the taxonomy, this ceases to be the case.

4.3 The Markov Model

A Markov model offers the advantages of simplicity, practical and immediate usability by workplace managers, and a well-developed body of knowledge and understanding derived from uses in math, engineering and other areas of the life sciences [4]. Such a model posits a number of underlying states of a system and a collection of probabilities of transition from any state to any other, including itself. We can now take the state transition counts, convert these to probabilities and then map them into the following model for group and team operation and evolution (Fig. 5 and 6).

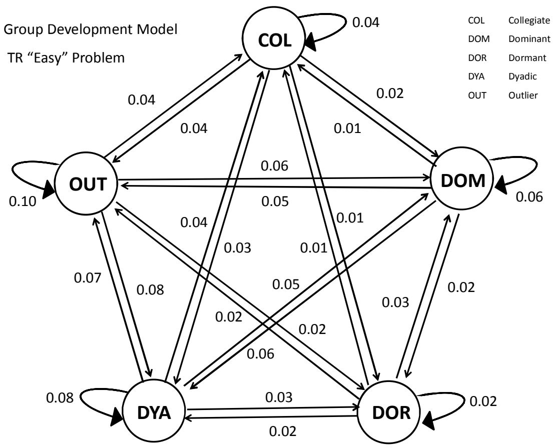

Fig. 5. Model for the "easy" case

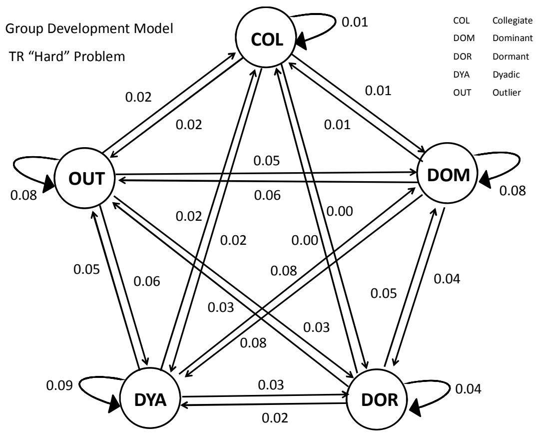

Fig. 6. Model for the "hard" case

Some preliminary observations about the dynamics of the subject team can be made from these models:

1. In the "easy" task, the team almost never transits from Collegiate to Dormant or Dormant to Collegiate. Therefore and if for example it should be undesirable for a team ever to be Dormant, with this dataset the safest state to try to engineer in a team would be Collegiate.
2. In the "hard" task, the bidirectional low-probability transition between Collegiate and Dormant is further accentuated, and simply never occurs. Thus this latent "forbidden" transition seems to be fundamental and is accentuated as the job becomes more demanding.
3. Although the team was forcibly started in the Dominant state by being instructed to select a leader, it does not remain in this state. In both the "easy" and "hard" tasks, Dyadic is slightly more stable state than Dominant. In the "hard" task, the hierarchical relationship between Dyadic and Dominant states is preserved, but Dormancy increases (perhaps owing to being "stumped" more often), Outlier behaviors reduce somewhat and Collegiate behavior drops significantly.
4. Outlier and Dyadic have a close relationship in the "easy" task, as do Dyadic and Dominant in the "hard" task. With clique leadership, minorities are often lost, dropping their engagement; and one overall leader still emerges frequently.

Now that we know the model is necessary and sufficient, and that it explains the observations, the remaining question is whether it has predictive value.

5 Discussion

The proposed taxonomy is also satisfying and robust from the standpoint of some 20 years' experience with team development in industry. We are all familiar with the "Dominant", one-leader team dynamic for example, as we are with leadership cliques in a "Dyadic" state; wholly engaged and disengaged teams in the Collegiate and Dormant states; and breakaway or disaffected minorities in the "Outlier" state. Examples of high-probability state transitions familiar to the experienced leader include the tendency of leadership cliques to disaffect some team members who feel ignored, and the rarity of truly collegiate and leaderless behavior. The model also applies well to an earlier study done on a large automotive company in which a rapid transition from Dominant to Outlier dynamics, which then became recursive, closed a manufacturing plant for two days at a cost of around $5M [4].

The model can also be shown to have predictive value, in that the same model was then applied to data from a previous experiment with submarine crews [3] and found to fit. Many of the same properties of team dynamics were verified with this data, and some new features applicable to submarine crews were also found.

We now also see the fusion offered by this new taxonomy between linear and nonlinear dynamics. This is especially useful in the mid-range organizational scale and apertures of observation favored by workplace managers in which the effects of linear, gestalt emergent behaviors and non-linear, non-gestalt behaviors in work teams become equally important.

The science and the brain itself are telling us that we need to model two gestalt states and three non-gestalt states. The gestalt, whole-of-team states are Collegiate and Dormant; in these states, the team can indeed be lumped together and considered as one, as older models assume for all states. The Dominant, Dyadic and Outlier states however are non-gestalt states, in which the granularity and fine structure of the team must be taken into account. The modern manager can simply use the five states as a model, confident that both linear and non-linear events are catered for.

The new model has immediate application in government and industry for practical managers at the line, middle, senior and top levels. Previous models of team evolution often do not match well with real-world observation, and are synthetic rather than analytic. An analytic model permits diagnosis and correction. Managers can readily spot whether a team is in a Dominant, Dyadic, Collegiate, Outlier or Dormant state and can be fairly confident of the likely futures, allowing good decisions to be made quickly. Passive observation of synthetic models offers no such call to action.

The model also lends itself well to recruitment, team-based interventions that have a measurable effect on productivity, change management and – perhaps most importantly – to the promotion of good and simplifying science in industry.

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