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Situational Understanding

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***Abstract*— This article examines cognitive processes engaged in situational understanding and outlines a framework for simulating such processes in computational systems (‘machine situational understanding’). Discussion focuses on elucidating key distinctions between ‘machine learning’ and ‘machine situational understanding’, and apprehending limitations of conventional AI methods (learning, reasoning) in approximating the capacity for situational understanding and/or facilitating situational understanding in the human operators.**

***Keywords*—situational understanding, mental modeling.**

I. Introduction: What is ‘situational understanding’?

The Webster‟s Dictionary defines *understanding* as “mental grasp; the capacity to apprehend general relations of particulars.” What kind of capacity is that, how does one go about the task of “grasping general relations of particulars”? What kind of cognitive difficulty is posed by the task? Figure 1presents three examples of “apprehending relations”, ranging in difficulty from trivial to challenging and complex.

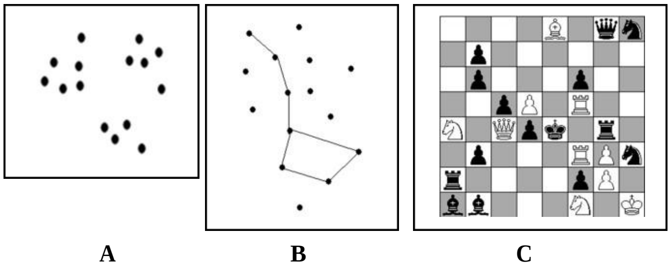

Figure 1. Grasping relations in a multitude of particulars. A) One can‟t fail seeing dots arranged in vertical columns. B) Relations are not so obvious. A group of dots (stars) is selected such that, if the dots are mentally connected, the resulting shape resembles a “big dipper” to some people (and a “big bear” to others). C) This position allows mate in 3 moves (Sam Loyd, circa 1859). The difficulty of apprehending relations in this arrangement is incomparably higher than in the other two.

“Apprehending relations” in Figure 1B is more difficult than in Figure 1A because, in part, relations in the latter encompass the entire set of elements (“particulars”) while in the former a subset needs to be selected. Solving the problem in Figure 1C also requires selection. The task of selecting pieces and apprehending relations is incomparably more difficult here because arrangements in Figure 1A and Figure 1B B are static while the one in Figure 1C is subject to changes and, as a result, relations reflect not so much the initial distribution of pieces across the board but rather the way the pieces are expected to move. Due to a large number of possible selection and movement choices, the solution-enabling relations might never come to mind. Figure 1 suggests defining „situational understanding‟ as a special case of *understanding* characterized by the following:

1. Seeking relations is motivated by the task.
2. Conditions remain in flux as the situation unfolds, relations need to be established in varying groups of situational elements (the “particulars”).
3. A small number of task-relevant relations can be „embedded‟ in a large number of irrelevant ones.
4. Timing is critical (think of facing situation 1C in a tournament).
5. Success (or failure) in apprehending relations can have decisive impact on the outcome of the task.

We shall return to the characteristics of situational understanding later, after considering in greater detail how these characteristics manifest in different situations.

II. How situational understanding impacts performance.

This section presents examples of performance degradation caused by deficits in situational understanding. Presentation is followed by a brief analysis.

a) The USS Stark incident.

On May 17, 1987, the *USS Stark*, along with 6 other Navy ships, was on a patrol mission in the Persian Gulf tasked with protecting Kuwaiti and Saudi oil tankers and international shipping lanes. Navigation in the area was under threat due to the on-going military conflict between Iran and Iraq. At 2109 Hour, the *USS Stark* was struck by two Exocet AM-39 anti-ship cruise missiles fired from an Iraqi F-1 Mirage fighter, killing 37 crewmembers and causing severe damage to the ship. The subsequent investigation revealed the following:

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- A U.S. Air Force Airborne Warning and Control System (AWACS) aircraft was in the area, relaying information to the *USS Stark*. At 1955 Hours, an aircraft located approximately 200 miles from the ship was detected by AWACS sensors, identified as F-1 Mirage fighter and labeled as “friendly.” Due to the “friendly” designation, crewmembers on the USS Stark decide that situation presents no imminent threat, giving no reasons to be concerned.

- At 2058 Hours, the fighter jet executes a sharp turn and increases speed in the general direction of the *Stark*. The potentially hostile intent demonstrated by the maneuver is not registered by the crew.

- At 2105 Hours, the aircraft turns directly toward the *Stark*. The information about this unambiguously hostile maneuver is picked up by sensors on both the AWACS and the ship but still not apprehended by the crew.

- At 2109 Hour, the *USS Stark* was struck by two Exocet AM-39 anti-ship cruise missiles.

Analysis of the sequence of events during the incident attributed the outcome to “inaccurate perception, comprehension, and projections” by the crewmembers [1].

b) The USS Vincennes incident.

On July 3, 1988, the U.S. navy cruiser *Vincennes* veered into Iranian territorial waters and mistakenly shot down Iran Air‟s Flight 655, killing 290 people on board. The subsequent investigation revealed the following

- An airplane lifting off from Iranian airport was picked up by the *Vincennes*‟ radar and identified as a commercial airliner. The plane was flying in Iranian airspace over Iranian territorial waters.

- The airliner was much larger than a fighter jet, and was ascending. In a later testimony, a crewmember who was standing behind the captain stated that “he never saw indications that the aircraft was descending.” Nonetheless, *Vincennes* fired two missiles one of which hit the plane.

- The commander of a nearby frigate, the *USS Sides*, reported that his radar showed an ascending, not a descending plane. The radar-tracking systems of the *Sides* and the *Vincennes* both covered the same airspace. When the records of the *Vincennes*‟ and the *Sides*‟ tracking systems were later reviewed, the information they showed was found to be identical.

A psychologist testifying before Congress suggested that the *Vincennes*‟ captain suffered from “expectancy bias” (i.e., selecting and organizing available data in such a way that the outcome matches the expectation). Due to such „expectancy bias‟‟, the captain and the crew ignored some of the available data and neglected to seek additional input, such as tracking the activity of other planes in the area which could have helped to determine whether the plane was in military airspace and could be a fighter jet, or whether it was in civilian airspace and was likely to be a passenger or cargo plane [2].

c) The battle of Waterloo.

In the battle of Waterloo in 1815, Napoleon, facing British forces under Wellington, dispatched a large contingent under General Grouchy to pursue the Prussians under General Bluecher and prevent them from joining Wellington. Due to weather changes and other unforeseen developments, artillery exchange started earlier than planned, with Napoleon expecting Grouchy to abandon pursuit of the Prussians at the sound of cannon fire and hurry to the main battlefield. Instead, Grouchy stuck to his orders: He caught up with and engaged a Prussian detachment. Bluecher sacrificed his rearguard and rushed to join Wellington.

In another episode in the same battle, French cavalry under General Ney was commanded to seize a village held by the British. Ney quickly succeeded, and believing that he found an opening in Wellington‟s defenses, pushed forward on his own initiative, provoking a heavy counterattack. Napoleon could not allow his elite cavalry to perish and sent cuirassiers from the center, leaving the center unprotected.

According to military historians, the arrival of the Prussians, weakening of the center and neutralization of the elite French cavalry decided the outcome of the battle. Note the following:

- Grouchy and Bluecher received the same data (the sound of the cannonade) but interpreted it and acted differently.

- Strictly following Napoleon‟s orders by Grouchy was a serious mistake but exceeding Napoleon‟s orders by Ney and acting on his own initiative was also a serious mistake.

In both episodes, decision timing was the determining factor (i.e., deciding to persevere and continue the course of action or to halt and change the course). As asserted by military thinkers throughout history, superior decision timing is the core cognitive capability that determines battle outcome and can neither follow nor can be expressed in any fixed rules:

> “…the ever-changeful form of things makes it necessary for the chief actor to carry in himself the whole mental apparatus of his knowledge, that anywhere and at every pulse beat he may be capable of giving the requisite decision from himself” (Von Clausewitz, [3]).

d) Air Traffic Control.

One of the most consequential mistakes an AT controller can make is overlooking the possibility of aircraft collision in the assigned space sector. Preventing collisions requires detecting intersecting flight trajectories early in the time interval before the possible collision, leaving sufficient time for informing pilots and executing avoidance maneuvers. Recording eye fixations of AT controllers as they were monitoring situations unfolding in the air space revealed the following [4]:

- In the controllers‟ mental representations, aircraft symbols on ATC displays were organized into groups roughly consistent with perceptual gestalts (see Figure 1A).
- Controllers were more likely to detect impending collision between aircraft residing in the same perceptual group than between those residing in different groups.

The distorting impact of gestalt grouping was more pronounced among novices; practice developed capacity to overcome the interference of gestalt mechanisms.

The above examples implicate deficits in situational understanding of At controllers that are common to all the described real-life situations. The following example concerns decisions in a fictitious situation throwing the benefits and deficits of situational understanding into a sharper relief.

e) Phenomenon.

In the movie "Phenomenon," the lead character (John) struggles to protect his vegetable garden from the invading rabbit. Patching and reinforcing the fence surrounding the garden bring no relief: invasions continue. Finally, having encountered extraterrestrials, the gardener receives a boost in his intellectual abilities allowing him to figure the things out: the rabbit was not coming from the outside but had been living in the garden. As a result, improving the fence did not serve to keep the rabbit out but, in fact, was blocking his escape.

What cognitive mechanisms are at work in all these situations? In a nutshell, the mechanisms a) combine objects into groups and b) determine relations between the groups and between objects inside and across the groups. The key notions are as follows: "Relations" boil down to different forms of coordination in the behavior of objects. Memory structures comprising objects, groups and relations between them constitute „mental models‟ yielding situational understanding. Start with the last example.

There are four participating „objects‟: fence, rabbit, garden (space inside the fence) and surrounds (space outside the fence). John‟s mental model habitually places rabbits in the surrounds and associates fence with the garden. The resulting mental model comprises two groups

((rabbit surrounds) (fence garden))

and entails coordination „fence up‟ → „rabbit out.‟ Failing expectation allows two choices: continue trying (keep improving the fence) or re-structure the model

((rabbit garden) (fence surround))

to obtain coordination „fence up‟ → „rabbit in‟. The newly grasped relation („rabbit‟ *resides in* ‗the garden‟) agreed with the data, explained the earlier disagreement and suggested remedial actions leading to the desired outcome. However, such re- structuring can require a level of cognitive effort that might or might not be accessible to the decision maker (hence, the boost from the extraterrestrials).

Arguably, the *USS Stark* incident was caused by a mental model placing Iraqi F-1 outside the military airspace surrounding the ship

((ship military airspace) (F-1 civilian airspace))

entailing expected coordination (F-1 is *no threat* to ship). The data (F-1 hostile maneuvers) did not agree with the expectation but mounting psychological stress and time constraints prevented the requisite re-structuring of the model.

By the same token, the *USS Vincennes* incident resulted from a mental model placing passenger airplane within the military airspace. This deficient grouping dominated the subsequent decision making and forced continuing the corresponding course of action (defending the ship, eliminating the threat), while ignoring the bare and severe disagreement with the data (ascending plane flying over Iranian territory).

French defeat in the battle of Waterloo was caused by disintegrated mental models forcing their holders to focus on local groupings and disregard intra-group interactions. Both General Grouchy and General Ney were preoccupied with local interactions in their respective groups

Ney: (French cavalry British contingent)
Grouchy: (French troops Prussian contingent)

to the detriment of the overall objective, as shown in Figure 2.

Groups in Figure 2 are disconnected which, of course, does not connote that either General was unaware of situational components outside the boundaries of his mental grouping.

However, situational awareness is only a prerequisite for understanding which, by itself, gives no guarantees that understanding will be attained. In that sense, neither General fully understood the situation.

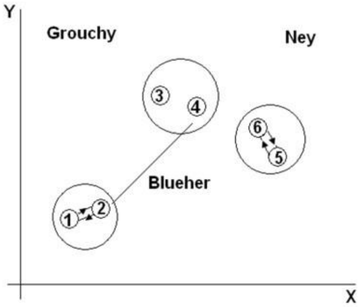

Figure 2. Mental models of both Generals comprised disconnected groupings. 1- French contingent under Grouchy, 2 – Prussian contingent under Bluecher, 3 - French forces under Napoleon, 4- British forces under Wellington, 5- French cavalry under Ney, 6 – British contingent. Line between two groups indicates a superior model (Blucher) accounting for inter-group relations.

Figure 3 depicts a mental model required for situational understanding (attributed to Napoleon who never lost a battle where troops were under his direct command).

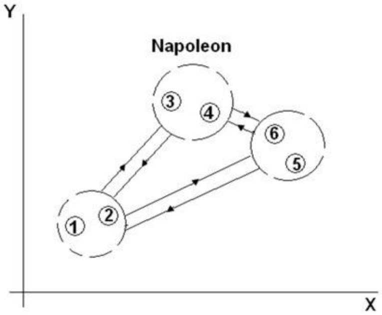

Figure 3. Situational understanding is yielded by mental models where all groups are integrated into a functional whole. As a result, decision maker„s attention can alternate between groups and make local decisions that also benefit or, at least, do not degrade conditions in the other groups.

Integrated mental models **enable global coordination of local decisions** [4]. Figure 4 underscores this idea.

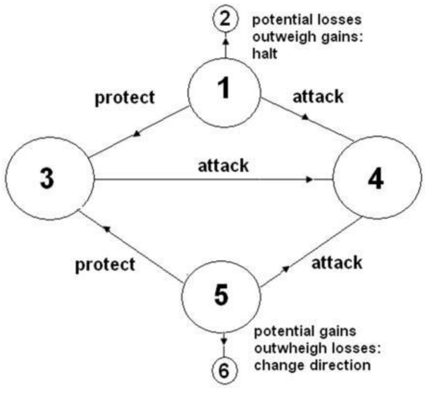

Figure 4. Integrated mental models establish relations between all situational components (object groupings) which makes possible globally coordinated decisions. For example, potential gains of continuing cavalry advance (1) can be balanced against the possibility of getting bogged down and thus depleting protection of the center (3) and reducing the strength of future attacks against the main British force (4). Global coordination would have halted Ney's advance and re-directed movement of Grouchy's contingent.

Situational understanding (or the absence of such) manifest in a similar fashion in various dynamic situations. For example, in chess, responding to temptation to capture a valuable piece can lead to losing the game in the next few moves while sacrificing a piece can open a shortcut to victory (similar to sacrificing the rearguard of Prussian contingent).

It might appear that complexity of integrated models, as in Figure 3, is far greater than that of fragmented models, as in Figure 2 (complexity is equated to the number of mental operations involved in exercising the model). In fact, exactly the opposite is true. For example, position depicted in Figure 1C can be extended into a prolonged game admitting an astronomically large number of variations and uncertain outcome, or can be won in 3 moves. Grasping the opportunity (the enabling subset of pieces) brings about complexity collapse; attaining the grasp is difficult while subsequent reasoning presents an incomparably lesser challenge. The scale of complexity collapse can be accessed from the following: chess machines had to reach the speed of about 10^8 evaluations per second in order to compete with human players capable of only a few evaluations per second.

It is interesting to note that the crucial benefit of situational understanding (complexity collapse) was recognized by Conan Doyle and cleverly exploited in the Sherlock Holmes saga: solutions of all the mystifying crimes resulted from picking up a few cues that, jointly, transformed bewildering arrays of disconnected facts into coherent models that both explained the facts and predicted actions of the criminal with accuracy sufficient for his interception and arrest. Grasp responsible for "cracking the crime" was not attained easily (requiring hours or days of contemplation, smoking and violin paying) while the subsequent reasoning was fast and simple.

To summarize: Situational understanding requires construction of mental models comprising objects, their behavior and inter-object relations. Such models must be stable enough to allow operations on them while conditions persist, and flexible enough to allow re-structuring when conditions change. Situational understanding enables the following

- explaining data and deriving predictions and response recommendations from the explanations,
- coordinating multiple decisions addressing different components in the situation,
- radically reducing complexity of decision making,
- extricating decision-relevant data (cues) from the mass of irrelevant data,
- other.

Summarily, situational understanding enables robust performance under unfamiliar and fluid conditions.

III. Understanding and learning.

Capacity for learning is ubiquitous across all the life forms on Earth, from plants to animals and humans. (e.g., plants that have experienced herbivory or disease respond more robustly to subsequent repeated insults than unchallenged plants [5]). However, the understanding capacity (ability to construct explanatory models and operate on them in the absence of sensory inflows) is unique to the humans. Understanding confers extraordinary adaptive advantages, as follows.

Learning allows organisms to prepare to likely future conditions before their onset. In that sense, learning predicts future, but only to the extent that future can be extrapolated from the past. That is, learning mechanisms capture regularities in the changing conditions and assume (by virtue of their inner working) that same regularities carry over from past history into the future. As a result, learning yields adaptive benefits for as long as the assumption remains valid, and can cause catastrophic failures when it no longer holds. The contribution of the understanding mechanism consists in overcoming the inertia of habit and prior learning when facing novel situations departing from the past regularities.

Due to a confluence of developments in the theory of algorithms, computer science, psychology and other disciplines in the middle of the last century, AI from the time of its inception has been downplaying the role of understanding in intelligent performance, focusing instead on learning and recognition. Accordingly, advances in AI over the last half century have been concentrated heavily in the area of machine learning, building on the foundation of perceptron algorithm (1957) and introducing adjustments yielding dramatic increases in its efficiency. In lieu of a more extensive discussion (see [6]), examples in this section will help to appreciate that recognition and learning, however efficient and robust, are not a substitute for understanding.

Figure 5 assumes that numerous photographs were taken of each and every participant during the battle of Waterloo, and afterwards presented for recognition to an advanced algorithm.

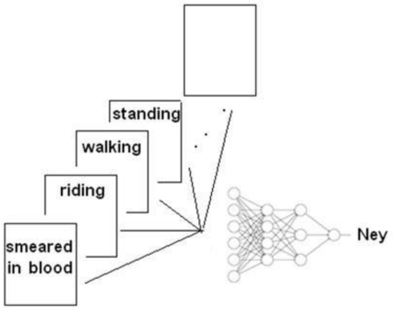

Figure 5. A well trained neural network reliably recognizes all the participants in all the snapshots taken during different episodes in the battle.

Assuming that performance is close to ideal (98% recognition reliability unconstrained by conditions and the number of objects) – what capability is still missing? Stated differently, besides selective targeting, what other advantages could such a system offer to Grouchy and Ney that could have changed the outcome of the battle? What would it offer to a military historian trying to apprehend the causes of French defeat?

Based on the suggestions in the preceding section, representation of behaviors and behavior coordination is missing. Methods are missing that would allow representing successions of states (behavior) exhibited by the participants

standing – walking – running – falling - …. (behavior)

and, crucially, the way behaviors were interwoven in the unfolding fabric of the battle. The limitation is inherent in the perceptron-based technology and, more generally, in the idea of "intelligence-via-learning-and-recognition" (advancing to 100% recognition reliability will provide no remedy).

To delve further into limitations of „learning without understanding‟ (or syntax without semantics [7]), consider the following. Understanding chess involves ability to apprehend behavior constraints and affordances intrinsic to configurations of pieces on the chess board. Assume now that a system learns regularities in chess, by being exposed to records of past games expressed in chess notation, e.g.

1.Bd7!Rg3 2.d6

The store of such records is (practically) unlimited but no other information (types of pieces, their behavior, rules of the game, structure of the chess board) enters the system. Technical feasibility aside, it is conceivable that learning produces a representation of game regularities (associations between symbols) in the system‟s memory such that, when presented with symbols representing a move, the system responds with symbols appearing to be a sensible counter-move. Clearly, despite the misleading appearances, the system‟s "mind" remains a complete void allowing one universal answer to question "**why**", regardless of the context.

Question: Why did you do B in response to A?
Answer: Because, more often than not, A associated with B.

Learned and/or genetically formed automatisms, once triggered, run their course regardless of the circumstances. For example, graylag geese display what appears to be sensible behavior: If an egg rolls out from the nest, they push it back to the nest. However, if the egg is snatched during the process, the behavior persists (the pushing movements continue) [8].

Learning without understanding remains oblivious to semantics, which makes performance fragile (breaks down when facing changing and/or unfamiliar conditions) and decisions inexplicable. By contrast, learning with understanding acquires semantics on top of syntax, thus making performance more robust and decisions explainable:

“Why did you decide to fire?
“The aircraft was descending towards the
ship thus presenting a threat.”

“Why did you decide not to fire?
“The aircraft was ascending away from the ship
thus presenting no threat” , etc.

To conclude, this section described shortcomings inherent in the AI approach to machine intelligence (**intelligence without understanding**). Arguably, multiple approaches can be formulated (along with the corresponding mathematical formalisms) promising to remedy the shortcomings. The next section sketches an approach motivated by a hypothesis concerning mechanisms of understanding in the human brain.

IV. Gnostron: approximating neuronal mechanisms underlying human understanding capacity.

Referring readers to [9], [10], [11] for a more detailed analysis, this section sketches some of the key notions in the gnostron proposal. Gnostron architecture includes neuronal pool and computational process organizing pool into a „virtual associative network‟ in the course of interaction with the environment (steaming input). Virtual network comprises five functional levels, as shown in Figure 6.

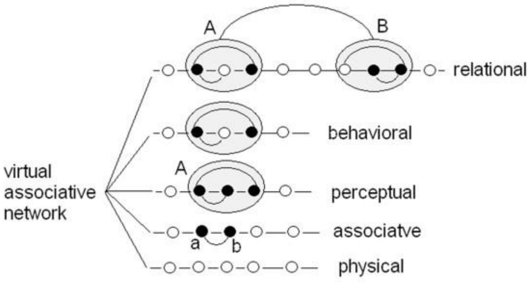

Figure 6. Virtual Associative Network.

In the physical level, connections are defined by synaptic contacts between neurons. In the associative level, associative (Hebbian) connections are formed based on synaptic contacts and conditions in the input (e.g., associative links forms between physically connected neurons **a** and **b** responding to different stimuli when those stimuli repetitively co-occur in the input). In the perceptual level, quasi-stable groups of tightly associated neurons (neuronal packets) emerge. Emergence of packets underlies the experience of perceiving objects (quasi-stable feature groupings). Behavioral level represents different response patterns in the already formed packets. Detecting different successions of such response patterns underlies the experience of apprehending object‟s behavior. Relational level establishes correspondence in the behavior of different objects (A and B), giving rise to the experience of grasping relation between them and thus having attained situational understanding. Figures 7 and 8 depict processes in the upper two levels.

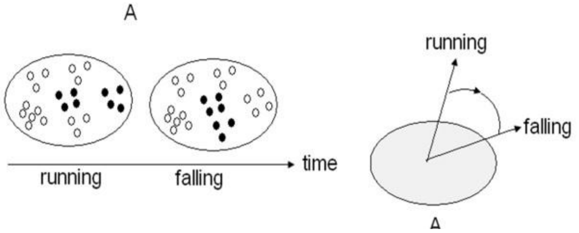

Figure 7. Behavior of objects (succession of object‟s states) is represented (encoded) by successions of changing firing patterns in the corresponding neuronal packets (e.g., object A changes state from „running‟ to „falling‟). If a cumulative response vector is computed on the neuronal packet, behavior variations correspond to different trajectories in the rotation of the vector.

Apprehending relations between objects involves establishing the form of coordination in the movement of the corresponding packet vectors.

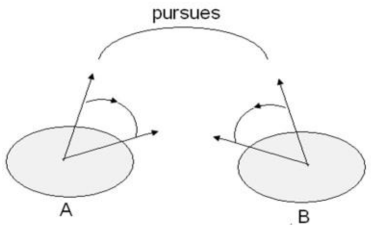

Figure 8. A particular form of coordination in the rotation of packet vectors corresponding to objects A and B establishes ***relation***, e.g., A *pursues* B.

The process is recursive: coordinated entities A and B can be combined into a composite entity C whose behavior can be coordinated with that of entity D, and so on.

(A B) → C, (C D) → F, ….

Finally, Figure 9 hypothesizes an integrated mental model for the battle of Waterloo.

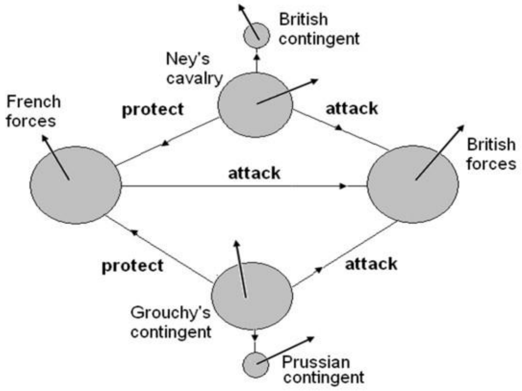

Figure 9. Mental model underlying situational understanding in the battle of Waterloo. The model comprises a set of coordinated packets. Exercising the model yields predictions of how changes in any component (rotation of the corresponding packet vector) impacts changes in all the other components.

V. Discussion.

Figure 9 illustrates the notion that situational understanding derives from mental models establishing mutual coordination in the behavior of participating entities, i.e., temporary regularities in the flow of changes experienced by the entities as the situation unfolds. Understanding is not attained by comparing present situation to earlier precedents, nor does it reduce to recognition. Exercising models produces adequate responses (decisions) that are dynamically fine-tuned to the changing conditions, although no pre-conceived algorithms are at work: the algorithms (1. Ney: halt; 2. Grouchy: change direction, etc.) are formulated on-line, after models are formed and stabilized enough to allow their execution [9].

The gnostron framework is anchored in a number of findings in neuroscience. In particular, movement coordination involves rotation of population vectors in the populations of neurons controlling the participating muscle groups [12]. The framework builds on these findings, hypothesizing that the same neuronal mechanism engaged in the organization of overt movements and manipulation of external objects is also involved in the manipulation of internal „objects‟. The hypothesis is consistent with some of the recent theories of neuronal processes underlying cognition [13], [14], [15].

Gnostron proposal suggests three lines of research:

1. The proposal makes a number of verifiable claims about biological neuronal mechanisms. Technology exists allowing to confirm or disconfirm these claims.

2. Gnostron formalism shifts the focus of analysis from recognition heuristics (vector mapping) to vector coordination. Some methods can be borrowed from cybernetics and other disciplines but problems remain that need to be addressed.

3. Understanding serves to optimize responses under unfamiliar and changing conditions. The hypothesis is that a) response optimization derives from the optimization of neuronal resources and b) thermodynamic efficiency is the force driving optimization in biological neuronal mechanisms [6], [9], [16]. Thermodynamically-driven processes can be computationally approximated in conventional computers, or emulated in intelligent machines of a new kind.

The range of potential applications in the long-term is hard to imagine. In the short term, systems can be designed endowed with a degree of situational understanding and acting autonomously **or** as decision aids. Decision aids that can find near-optimal responses and explain them to the users might be of particular value under time-limited and stressful conditions likely to provoke emotionally biased reactions of human operators (stated differently, the aid can provide some of the benefits of reflective thought and careful analysis when time pressure and circumstances deny those to the operator [17]). Another critical function of the aid can be filtering and organizing data for the operator, preventing floods of irrelevant information. Summarily, these functions can provide aid sufficient for shifting the outcome of the situation in the favorable direction [18], [19].

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