Enhancing Intuitive Decision Making through Implicit Learning

Joseph Cohn, Peter Squire, Ivy Estabrooke, and Elizabeth O'Neill

Office of Naval Research, USA
Joseph.Cohn@navy.mil

Abstract. Today's military missions pose complex time-constrained challenges, such as detecting IED emplacements while in a moving vehicle or detecting anomalous civilian behaviors indicative of impending danger. These challenges are compounded by recent doctrinal requirements that require younger and less-experienced Warfighters to make ever-more complex decisions. Current understanding of decision making, which is based on concepts developed around theories of *analytic* decision making (Newell and Simon, 1972), cannot effectively address these new challenges since they are based on the notion of enabling experts to apply their expertise to addressing new problems. Yet, there are actually two types of recognized decision making processes, *analytical* and *intuitive*, which appear to be mediated by different processes or systems (Ross et al, 2004; Evans, 2008; Kahneman & Klein, 2009). *Analytical* decision making is mediated by processes that reflect a sequential, step-by-step, methodical, and time-consuming process. To be effective, *analytic* decision making appears to require domain expertise. In contrast, *intuitive* decision making relies upon a more holistic approach to processing information at a subconscious level (Luu et al, 2010). The thesis of this paper is that unlike *analytic* decision making, effective *intuitive* decision making does not require domain expertise but, rather, can be enhanced through training methods and technologies. This paper will explore ways in which the results from a range of studies at the behavioral, cognitive and neurophysiological levels can be leveraged to provide a comprehensive approach to understanding and enabling more effective *intuitive* decision-making for these non-experts.

Keywords: Cognitive Modeling, Perception, Emotion and Interaction, Intuition Decision Making, Implicit Learning.

1 Introduction

The traditional understanding of intuition suggests that it can guide the judgment process by assisting with the discovery of plausible solutions from which to choose (cf Bowers, et al. 1990). This characterization of intuition - and many others that follow from it (e.g Kahneman & Klein, 2009) - assumes a high level of familiarity with the information being detected. Yet a growing body of results ranging from the biological (mainly, neural) to the cognitive (Lieberman, 2000; Jung-Beeman et al., 2004;

D.D. Schmorrow and C.M. Fidopiastis (Eds.): AC/HCII 2013, LNAI 8027, pp. 401–409, 2013.

Luu et al 2010) suggests that pre-existing expertise, which requires years of practice to attain (Ericsson et al, 1993) may not be a key requirement for developing intuitive decision making processes. These studies suggest that intuitive decision making processes share some of the same underlying neural structures and cognitive processes as implicit learning (Frensch, 2003; Lieberman, 2000, 2007). By acquiring domain knowledge through implicit learning, one may be able to automatically strengthen, at the neural, cognitive and behavioral levels, the same capabilities that are needed for effective intuitive decision making (Figure 1), making intuition a strong candidate for enhancement through training.

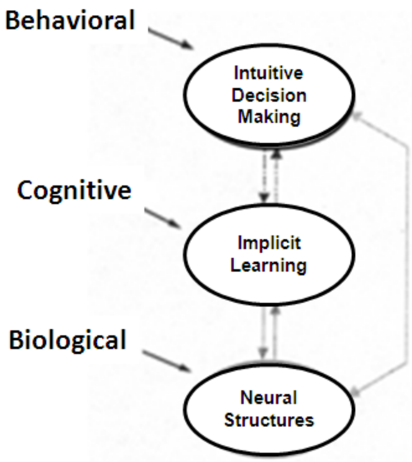

Fig. 1. Intuition relies on multiple layers of systems, from the biological to the cognitive to the behavioral. After Newell, 1993; Lieberman, 2000.

In order to develop these training capabilities, ***four challenges*** that are key to understanding and enhancing *intuitive* decision making must be addressed and understood: 1) Combining advances in measuring performance at multiple representation levels (e.g., neural, cognitive and behavioral) with advances in simulation–based paradigms for assessing decision making to understand the foundations of *intuitive* decision making; 2) Leveraging advances in cognitive modeling and machine learning techniques to represent individual *intuitive* decision making processes; 3) Developing an implicit learning based approach for enhancing *intuitive* decision making; and, 4) Combining these efforts, through scenario/simulation based training, to test and validate the hypothesis that implicit learning can enhance *intuitive* decision making for one or more operationally valid tasks. The remainder of this paper will discuss each of these challenges and possible solutions in greater detail.

1.1 Defining Intuition

Decision making is decomposed into two types or categories: *analytic* and *intuitive*. At the behavioral level *analytic* decision making is characterized by properties such as deliberate and often lengthy periods of processing information, leading to a final result. At the cognitive level, *analytic* decision making seems to require intentional or goal-oriented information processing combined with a clear potential for being impacted by other cognitive processes – e.g. working memory. Finally, at the neural level, *analytic* decision making seems to be driven by a series of neural structures collectively acting as part of an (ad hoc) network. These structures include: Lateral Pre Frontal Cortex; Dorsomedial Pre Frontal Cortex; and Medial and Lateral Parietal Cortices and (Luu et al 2010; Lieberman, 2000, 2007; Bowers 1990). Perhaps most importantly, though, *analytic* decision making has shown itself to be accessible to a wide range of performance enhancement methodologies (Ericsson et al, 1993).

Conversely, *intuitive* decision making at the behavioral level is characterized by properties such as seemingly non-deliberate and fast operating information processing, seemingly at the pre conscious level. At the cognitive level, *intuitive* decision making seems to be cued by recognizable characteristics of the information being processed. At the neural level, *intuitive* decision making seems to organize brain networks for more advanced processing – acting as a ‘coherence generator’ for external information detected through sensory organs. Importantly, there have been only limited efforts focusing on enhancing *intuitive* decision making.

Because *analytic* decision making has proven to be more amenable to enhancement, the vast majority of efforts to improve overall decision making performance have focused on it. This bias towards *analytic* decision making belies the potential benefits to be gained by enhancing *intuitive* decision making. *Intuitive* decision making processes appear to provide a quick connection to the Limbic system (‘gut responses’) coupled with slower connections to frontal cortex and executive functions (Luu et al, 2010) potentially. As well, evidence suggests that intuition activates the formation of semantic networks in the brain. This means that *intuitive* decision making may actually set the stage for the detailed assessment of the benefits of taking those actions enabled by *analytic* decision making (Evans, 2008; Luu et al, 2010).

Figure 2a shows one way of envisioning this synergy between *intuitive* and *analytic* decision making, based notionally on the Human Information Processing notion of Parasuraman & Sheridan (2000) (Figure 2a). Early on the *intuitive* decision making system is activated, helping process key features of information while also priming the *analytic* decision making system. Later on, the *analytic* decision making system is activated, making sense of the information, enabling the decision maker to guide the process.

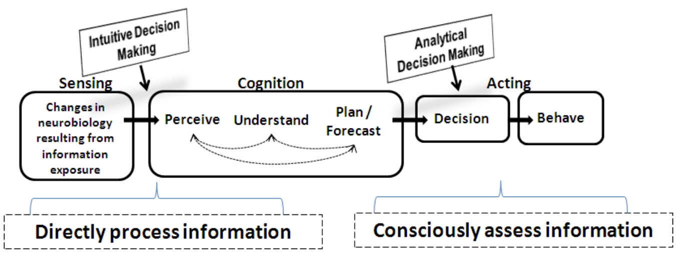

Fig. 2a. One view on how the two decision making systems may work together

Figure 2b provides a neural perspective on this synergy. When information requiring a decision and subsequent action is presented to an individual, initial features like contour and shape are registered by neural structures in the Temporal-Parietal-Occipital region (0 ms to ~250 ms). At approximately 250 to 300 ms other neural regions become activated, including those both in the limbic region, triggering the 'gut response' which is a hallmark of intuition, as well as those in cortical regions responsible for activating executive functions.

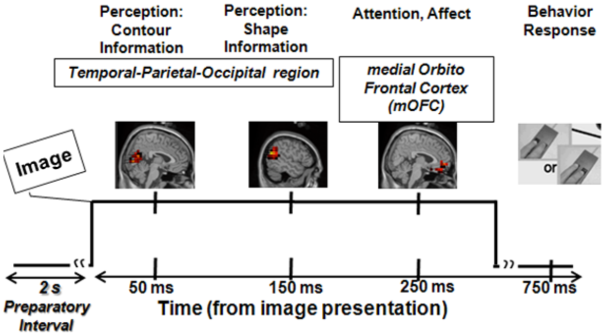

Fig. 2b. A neural level perspective on how the two decision making systems may work together. See text for details

1.2 Facilitating Intuition

The above discussion leads to two important points regarding enhancing human decision making. First, it suggests that we have a strong enough grasp of what intuition is, across different levels or representation, that we may consider it a ripe target for enhancement. Second, it suggests that by improving intuition we may streamline the decision making cycle. The critical question is how can we facilitate intuition?

Our starting point in addressing this question can be summed up by a quote from Reber, 1989: "To have an *intuitive* sense…is to have gone through an implicit learning experience." In order to develop one's *intuitive* capabilities, one must have moved through a type of learning known as implicit learning. In turn, this suggests that one may enhance one's *intuitive* capabilities through implicit learning. But what is implicit learning and why might it lead to enhanced *intuitive* decision making performance?

As Frensch & Runger (2003) define it, implicit learning is: "Learning complex information in an incidental manner, without awareness of what has been learned." Implicit learning emphasizes the role of associative learning mechanisms, coordinating action amongst different cognitive processes. Implicit learning exploits statistical dependencies in the environment, meaning that it is driven by certain kinds of features – or pattern structures-detected in information streams. Implicit learning leads to the generation of implicit knowledge as abstract representations (Seger, 1994) which provides the basis through which implicit knowledge can generalize to other contexts.

As Table 1 shows, the similarities between implicit learning and *intuitive* decision making are striking. Both processes seem to occur at a preconscious or unguided level. Both processes appear to rely on recruiting different processes and or structures across the brain (Luu et al 2010). Both involve a level of pattern detection in the information stream being processed (Bowers, 1990). Lastly, both focus on transforming information into generalizable and actionable knowledge (Bowers, 1990). These similarities are equally striking when the neural structures underlying both processes are compared. Recent findings suggest that many of the neural structures that support intuition also support implicit learning (Luu et al 2010; Lieberman, 2000, 2007; Bowers 1990).

Table 1. Some similarities between implicit learning (Left) and intuitive decision making (Right)

Preconscious	
Coordinated Action	
• **Implicit learning emphasizes the role of associative learning**	• **Intuition coordinates activity across the brain**
Pattern Detection	
• **Implicit learning exploits statistical dependencies in the environment**	• **Intuition requires perceiving coherence at a preconscious level**
Generalization	
• **Generates implicit knowledge as abstract representations for broader application**	• **Provides abstract 'hunches' about the nature of the pattern in question**

Together, these findings suggest that from a neural, cognitive and behavioral perspective we may be able to facilitate intuition through implicit learning. The question then becomes how best to do this. We propose a four step process that includes:

- Characterizing *intuitive* decision making and implicit learning across neural, cognitive and behavioral levels of representation
- Representing *intuitive* decision making through cognitive models in order to guide implicit learning techniques.
- Applying scenario based training techniques to develop implicit learning approaches that enhance *intuitive* decision making.
- Testing the hypothesis that implicit learning facilitates *intuitive* decision making.

1.3 Techniques for Characterizing Intuition

Traditionally, *intuitive* decision making has been studied at the behavioral level only, relying on simple reaction-time measures to infer when *intuitive* decision making has occurred (Hodgkinson et al, 2008). Recent developments in the cognitive neurosciences suggest that it is possible to characterize intuition across multiple levels of representation, thereby gaining deeper insight into how intuition works. For example, Lieberman et al (2007) showed that the two decision making systems are actually driven by two separate networks of brain areas while Luu et al (2010) demonstrated that it was possible to directly correlate decision making behaviors with neural markers derived from activity in these two systems to determine when intuition occurred and when it did not.

There are a wide range of technologies that can be used to detect intuition. These technologies can be categorized in terms of 'Data Source' 'Measurement Time', and 'Data Channels'. Figure 3 provides a representation of some common types of detection technologies in terms of these three parameters. On the 'Data Source' axis, the data sources that may be accessed to characterize intuition range from subcellular processes and individual nerve cell action, to measured behavior outcomes. On the 'Measurement Time' scale, the different time scales underlying the processes represented by each of these data sources are shown. On the 'Data Channels' axis, the number of measurable Data Source 'units' is represented. For example, the potential number of ion channels that could be measured, limited by the size of probes, or the number of behavior responses, limited by the number of metrics that can be associated with a given action.

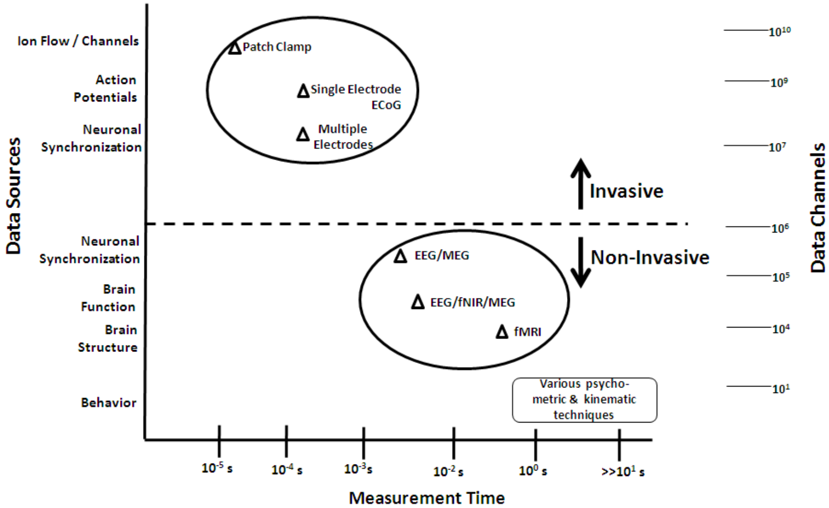

Fig. 3. Detection technologies

1.4 Techniques for Modeling Intuition

In order to make the characterization of intuition accessible to new training technologies an "executable" representation of these data must be developed. This requires both new approaches to decoding the performance data and to representing it as a model. Over the past several years, various machine learning techniques have been developed that help organize large, multi-scale sets of time series data into information classifiers. These multivariate decoding routines (Mitchell et al 2004) have the ability to take into account the full spatial pattern of brain activity, cognitive measures and behavioral outcomes and appear to be transferrable to other, never-before encountered individuals, with little reduction in accuracy (Shinkareva et al 2008). In practice, it is expected that the initial classification routines will require a wide range of data sets and types, encompassing biological, cognitive and behavioral.

These classification approaches provide the rectified data necessary for building models of human performance. One approach that continues to gain momentum is to take existing cognitive models and link them to neural data. For example one of the better known cognitive modeling approaches is ACT-R (Anderson, 1996). In its executable form, the timing and sequencing of ACT-R's model components is based on observed behaviors, and the output is typically timing and accuracy predictions. Recently, studies performed by Anderson et al (2008) have demonstrated which neural regions correspond to which elements of their modules and buffers, opening up the possibility for a direct link between neural data and a proven cognitive modeling approach. Other approaches focus on developing *neurocognitive architectures* that are specifically tailored to fuse data captured from different sources to create generative hybrid models (see Figure 4). These approaches blend top-down and bottom-up approaches to innovatively combine context with various types of cognitive and neural measures to model overall user performance. Using machine learning and artificial intelligence routines, these approaches can adapt their models using past behaviors, specific actions taken and outcomes realized.

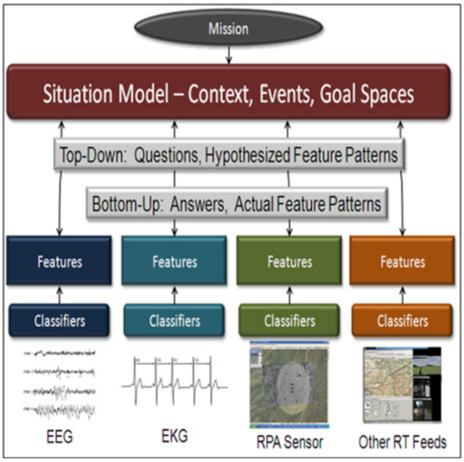

Fig. 4. An example neurocognitive architecture. Shown are both the *top-down* aspects, like hypothesis generation about patterns in collected data as well as *bottom-up* processes, like the data fusion and classification (with permission from Dr Webb Stacy, Aptima).

1.5 Scenario-Based Training

The classical understanding of intuition is that it requires a high degree of domain expertise. By some estimates, achieving such expertise may require up to ten years of intense exposure to any number of a wide range of practical 'training' exercises, which is well outside the training cycle in which effective Marine decision makers are developed. As envisioned here, *intuitive* decision making develops as a result of the 'strengthening' of connections with specific structures in the brain, like the basal ganglia, combined with the development of specific types of targeted training, collectively known as implicit learning. In practice, implicit learning is experiential and interactive, instead of didactic and classroom based. Therefore, it seems reasonable to focus on training technologies like virtual environments or serious games to provide the "experiential" component, using models of an individual's *intuitive* processes to modify the "interactive" component. The overarching training methodology to be employed will be Scenario Based Training (SBT), which emphasizes embedding training approaches within an evolving and dynamic scenario rather than delivering it through a series of static lessons (Oser et al 1999).

1.6 Measuring Success

There are two possible approaches for measuring success in this kind of effort. The first is to demonstrate that the neural structures that are active during implicit learning are also active during intuition; that in the absence of implicit learning there are different / distinct patterns of neural activity during an *intuitive* decision making task; and that in control tasks in which neither implicit learning was provided or *intuitive* decision making required, these structures are minimally active. This approach will essentially compare measures of neural activity across different task conditions.

The second is to show that, under those conditions in which implicit learning was provided and *intuitive* decision making was present, there is a significant improvement in decision making compared to other conditions as represented for instance by a shift in the form of receiver operator characteristic curves.

2 Summary

This paper proposes a new approach for enhancing *intuitive* decision making in novices, outlining four areas to address in order to develop training technologies for *intuitive* decision making. First, the nature of *intuitive* decision making must be characterized, at the neural, cognitive and behavioral levels. Second, these characterizations must be integrated into a single model that accurately represents these characterizations providing the foundation for developing training technologies. Third, the resultant model must be implemented into a training technology that demonstrably enhances an individual Warfighters' *intuitive* decision making capabilities. Finally, the effectiveness of this approach must be determined through a range of assessment techniques.

References

1. Anderson, J.R.: ACT: A simple theory of complex cognition. American Psychologist 51, 355–365 (1996)
2. Anderson, J.R., Carter, C.S., Fincham, J.M., Qin, Y., Ravizza, S.M., Rosenberg-Lee, M.: Using fMRI to Test Models of Complex Cognition. Cognitive Science 32, 1323–1348 (2008)

3. Bowers, K.S., Regehr, G., Balthazard, C.G., Parker, K.: Intuition in the context of discovery. Cog. Psyc. 22, 72–110 (1990)
4. Ericsson, K.A., Krampe, R.T., Tesch-Romer, C.: The role of deliberate practice in the acquisition of expert performance. Psychological Review 700, 379–384 (1993)
5. Evans, J.: Dual-processing accounts of reasoning, judgment, and social cognition. Ann. Rev. Psyc. 59, 255–278 (2008)
6. French, P.A., Runger, D.: Implicit Learning. Current Directions in Psychological Science 12, 13–18 (2003)
7. Hodgkinson, G., Langan-Fox, J., Sadler-Smith, E.: Intuition: A fundamental bridging construct in the behavioral sciences. British Journal of Psychology 99(1), 1–27 (2008)
8. Jung-Beeman, M., Bowden, E.M., Haberman, J., Frymiare, J.L., Arambel-Liu, S., Greenblatt, R., et al.: Neural activity when people solve verbal problems with insight. PLoS Biology 2, 500–510 (2004)
9. Kahneman, D., Klein, G.: Conditions for intuitive expertise: A failure to disagree. Am. Psyc. 64(6), 515–526 (2009)
10. Lieberman, M.D.: Intuition: A social cognitive neuroscience approach. Psychological Bulletin 126(1), 109–137 (2000)
11. Lieberman, M.D.: Social cognitive neuroscience: A review of core processes. Annual Review of Psychology 58, 259–289 (2007)
12. Luu, P., Geyer, A., Wheeler, T., Campbell, G., Tucker, D., Cohn, J.: The Neural Dynamics and Temporal Course of Intuitive Decisions. Public Library of Science (2010) (in Press)
13. Mitchell, T.M., Hutchinson, R., Niculescu, R.S., Pereira, F., Wang, X., Just, M., Newman, S.: Learning to Decode Cognitive States from Brain Images. Machine Learning 57, 145–175 (2004)
14. Newell, A., Simon, H.A.: Human problem solving. Prentice-Hall, Englewood Cliffs (1972)
15. Oser, R.L., Cannon-Bowers, J.A., Salas, E., Dwyer, D.J.: Enhancing human performance in technology-rich environments: Guidelines for scenario based training. In: Salas, E. (ed.) Human Technology Interaction in Complex Systems, vol. 9, pp. 175–202. JAI Press (1999)
16. Parasuraman, R., Sheridan, T.B., Wickens, C.D.: A model for types and levels of human interaction with automation. IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans 30, 286–297 (2000)
17. Ross, K., Klein, G., Thunholm, P., Schmitt, J., Baxter, H.C.: The Recognition-Primed Decision Model Mil Rev., p. 6–10 (2004)
18. Reber, A.S.: Implicit learning and tacit knowledge. Journal of Experimental Psychology: General 118, 219–235 (1989)
19. Shinkareva, S.V., Mason, R.A., Malave, V.L., Wang, W., Mitchell, T.M., Just, M.A.: Using fMRI brain activation to identify cognitive states associated with perception of tools and dwellings. PLoS ONE 3, e1394 (2008)