# Cognitive Augmentation for Coping with Open-Source Intelligence (OSINT) Overload

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The goal of intelligence community analysts is to provide information summaries to policymaker customers to support their decision-making. While all-source intelligence has traditionally relied primarily on HUMINT (intelligence from human sources), SIGINT (intelligence from intercepted communications), and IMINT (intelligence from overhead imagery), OSINT (intelligence from open sources like the internet) is increasingly contributing to intelligence assessments (Benes, 2013; Tabatabaei & Wells, 2016).

Open Source Intelligence has been defined (Sec. 931 of Public Law 109-163, entitled "National Defense Authorization Act for Fiscal Year 2006) as being "Produced from publicly available information that is collected, exploited, and disseminated in a timely manner to an appropriate audience for the purpose of addressing a specific intelligence requirement." Defined in this manner, it can include such materials as academic publications, news media, forum discussions, web archives of corporate and government documents, video postings, and social media. In order to facilitate usage of these new sources of information, the Office of the Director of National Intelligence established the Open Source Center in 2006 (https://fas.org/irp/dni/osc/).

OSINT has a number of advantages over traditional collection methods. The first is that it is relatively inexpensive. The second is that it can be collected from allies (e.g., to better understand their trade policies) without risk of diplomatic repercussions. The third is that they complement traditional intelligence sources by providing broad insights into a society (to help predict events like the Arab Spring) and into the overt activities of non-state actors (such as terrorists and drug cartels). The fourth is that some adversary activities by their nature operate in the open media (e.g., disinformation campaigns and recruitment efforts) and are therefore best monitored via OSINT.

Despite the advantages of OSINT, there are significant drawbacks as well. The greatest drawback is simply the sheer volume of open source materials. For example, on January 10th, 2017 there were about 500 million new Tweets on Twitter, 75 million new blog posts to Tumblr, 1.1 billion websites, and 1.8 billion Facebook users (internetlivestats.com/twitter-statistics). Computerized methods are needed to assist analysts in efficiently sorting through such large amounts of material rapidly.

A recent government report on “Preparing for the Future of AI” highlights the importance of human-machine teaming. Most previous efforts that have focused on human-machine teaming were conducted in a context of cognitive-motor performance such as, but not limited to, the assessment of trust in automation or cognitive workload during flight task (e.g., Oh et al., 2015) as well as brain computer interface for rehabilitation. However, the development of human-machine interaction in a context of information retrieval by a human operator based on the derivation of brain biomarkers is much more limited. As such, here we propose an alternative information centric form of human-machine teaming which is consistent with the recent “National AI R&D Strategic Plan” which states that “intelligent systems should have the ability to augment human cognition, knowing which information to retrieve when the user needs it, even when they have not prompted the system explicitly for that information”.

One possible approach is by using a combination of physiological monitoring and computerized assistance to facilitate analyst performance, which has been termed Augmented Cognition (Stanney et al., 2009). Such methods have already been investigated in the domain of IMINT, with a number of reports funded by the now concluded DARPA-funded Neurotechnology for Intelligence Analysts program (Kruse, Boyd, & Schulman, 2006; Miranda et al., 2015). In these studies, the participants performed triage (identifying images for further in-depth examination) mostly on a stack of satellite images provided by the National Geospatial Intelligence Agency (NGA). While the images were rapidly serially presented to the participants, electroencephalography (EEG) data were collected and used to determine if the neural responses could improve on the overt button presses. Promising improvements in speed (Bigdely-Shamlo, Vankov, Ramirez, & Makeig, 2008; Huang, Erdogmus, Pavel, Mathan, & Hild, 2011; Mathan et al., 2006; Meng, Merino, Robbins, & Huang, 2014) and accuracy (Poolman, Frank, Luu, Pederson, & Tucker, 2008; Sajda et al., 2010) were reported.

There is a need to extend these promising IMINT results to the text sources that comprise the majority of OSINT materials. Text materials are much more complex and require a different approach. In RECON (Ross, Morris, Ulieru, & Guyard, 2013), a framework for intelligence analysis sense-making proposed by Defense R&D Canada, computerized support is provided at a number of levels, namely brain-computer interfaces (monitoring user state), human-computer interaction (enhancing presentation of information), context-awareness (taking into account user goals to filter information), and case-based recommendation (suggesting leads based on prior user sessions). Within such a framework, measures like EEG, eye-tracking, autonomic physiological arousal, and functional near-infrared spectroscopy can potentially be deployed into the analyst workplace (Stanney et al., 2009).

Several studies demonstrate the potential for applying cognitive augmentation to OSINT text materials while also illustrating the limitations of existing research. One study (Chow & Gedeon, 2015) showed that measures of autonomic arousal (even without eye-tracking) were sufficient to classify document relevance nearly as well as behavioral responses (75% compared to 79%) but did not investigate how such measures could complement rather than just supplement behavioral responses. Potentially such autonomic measures could also detect when stress levels are too low or too high and enable automatized compensation. Gwizdka (2014) demonstrated that eye-tracking data alone can achieve 72% accuracy on binary text document classification and 67% using pupil dilation alone (for reading short news stories). Gwizdka and Zhang (2015) used eye-tracking on OSINT sources (on realistic viewing and reading on the web) and achieved 61% classification accuracy of relevant web pages. This accuracy could be plausibly improved if types of web pages, their layout and types of web information objects (e.g., text or images) are considered. Eugster and colleagues (2014) used EEG (without eye-tracking) to predict the fine-grained relevance of words to a topic. In a follow-up study (Eugster et al., 2016) they demonstrated that the EEG classifiers from reading a text could then be used successfully to select relevant wikipedia articles, but not under realistic reading conditions. Frey and colleagues (2013) used EEG synchronized with eye tracking to predict the relevance of documents to a topic. Furthermore, they reported measurable responses to single target words. However, this study did not examine the viability of single-trial analysis ultimately required for workplace application.

In summary, research on translating cognitive, computer science, and neuroscience methods into the analyst workplace could provide a strong return on investment for OSINT productivity. Through detection of validated biomarkers that are indicative of attention capture and relevance in response to specific text stimuli, the machine interface can then effectively filter and select text from a potentially overwhelming volume of information so as to aid the human operator in the navigation and processing of useful information while avoiding the burden of excessive cognitive load, distraction, and the omission of critical information. Additionally, such research could enhance basic science understanding of the reading process, with potential benefits for education and treatment of reading disorders like dyslexia. In the second call for papers we will describe our recent experiments with eye-tracking and EEG in a natural reading task.

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