Toward a Wearable, Neurally-Enhanced Augmented Reality System

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Abstract. Augmented reality systems hold great promise, but as they become more complex they can become more challenging to use. Incorporating neural interfaces into augmented reality systems can dramatically increase usability and utility. We explore these issues in the context of Equinox Corporation's Night REAPER™ system—an augmented reality system for dismounted warfighters. We describe the current Night REAPER system and then survey some of the potential enhancements and unique design challenges associated with the addition of a neural interface. Signals, sensors, and decoding techniques for the system's brain-machine interface are discussed.

Keywords: augmented reality, brain-machine interface, wearable systems.

1 Introduction

Augmented reality (AR) systems are becoming increasingly widespread, and have countless consumer, industrial, medical, and military applications. The proliferation of inexpensive sensors has greatly increased the quantity of information that can be incorporated into an AR system. While this development holds great promise, the increased complexity of AR systems poses a challenge for usability. Each sensor and operating mode is accompanied by a combinatorial explosion of configurations from which the user must select. Compounding this problem is the notion that in many environments, such as the operating room or the battlefield, AR systems are most useful if they can be managed in a hands-free manner. Furthermore, the cognitive load associated with operating a complex AR system can distract the user from the very task that it is meant to facilitate.

Incorporating a neural interface into AR systems can greatly increase their usability and utility. A user can potentially control the system with their brain activity, permitting quick, hands-free execution of tasks such as choosing from one of several discrete options. Beyond this, there is also the possibility of a deeper connection between brain and machine. We can imagine designing a system where the user's brain and an onboard computer communicate bi-directionally and work synergistically to solve problems that neither could solve on its own. For example, in a nighttime

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surveillance task, the AR system could use a night vision sensor to make subjects visible, while the user's brain performs the more challenging task of detecting a subject of interest. The system observes a correlate of the detection in the user's brain activity and then zooms the camera in on the subject. Interestingly, the use of brain activity may not even require the user's conscious awareness.

We are particularly interested in wearable AR systems that are untethered and permit the user to move freely through a dynamic environment. Obviously, such systems are subject to strict size, weight, and power constraints. They require miniaturizing and making portable the brain-machine interface, as well as integrating it with the head-mounted display of an AR system. In this paper we will introduce a specific application—the Night REAPER™ system for dismounted warfighters—and describe how it can potentially be enhanced by a neural interface. We will also describe some of the unique design challenges that arise in this application. That said, the neurally-enhanced sensory augmentation concepts we will discuss are general and are applicable to a wide array of applications, including systems that facilitate the operation of vehicles or the performance of computer assisted-surgery.

2 Night REAPER Augmented Reality System

Over the past six years, Equinox Corporation has been developing the Night REAPER™ (Rapid Engagement Aim Point viewER) system, a wearable AR system for dismounted warfighters (Figure 1). Through the use of advanced signal and image processing, it harnesses the strengths of intensified night vision imaging and thermal imaging to deliver a detailed situational picture. Unlike other image fusion platforms, Night REAPER combines inputs from sensors that are located separately and moving independently of one another. Using a head-mounted display (HMD), the user can see the imagery from his thermal weapon sight (TWS) co-registered in real-time over a helmet-mounted intensified night vision field of view. This allows the user to seamlessly transition from navigation to target detection, identification, and, ultimately, engagement. In navigation mode, the user relies primarily on his wide-field head-mounted night vision device, while using the Night REAPER's ability to overlay the TWS output as a "thermal flashlight" that allows quick detection of targets (Figure 2). If the target is to be engaged, Night REAPER can provide assistance in the form of range information and other ballistic calculations. All the while, the user has access to additional sources of information such as maps and network-centric assets that can be displayed at will.

2.1 Vision for a Neurally-Enhanced Night REAPER System

We propose a neural interface for the Night REAPER system that allows for a seamless integration of advanced sensors, network-centric assets, and computational capabilities with the user's senses. The user manages the system with their brain activity, bypassing the need to provide explicit input. Furthermore, brain activity is coupled to an on-board computer vision system, enabling tasks that the computer is unable to do alone. A block diagram of the proposed system is depicted in Figure 3.

Fig. 1. Current Night REAPER system with labeled components

Fig. 2. Night REAPER augmented reality view. The grayscale background represents the intensified imagery, and the color overlay represents the imagery from the thermal weapon sight.

Consider the target detection-identification-engagement sequence under a neurally-enhanced Night REAPER system. While the user is on patrol, he subconsciously spots a target of interest. Through the neural interface, the system becomes aware of this detection event and cues the user's conscious perception by highlighting the potential target on the HMD. Sensing that the user intends to identify the potential target, the system enhances the target's appearance. It also provides additional information, such as target GPS coordinates in conjunction with network-acquired information about friendly troop disposition in the area. When the decision to engage the target is made, the system seamlessly transitions to targeting mode, where perhaps the full TWS field of view is expanded to fill the HMD and ballistic computation assistance appears as part of the reticle. Throughout this entire process, the user is not required to shift his attention to system management. All system decisions are managed directly through a neural connection, reducing the cognitive load and increasing efficiency in a complex task.

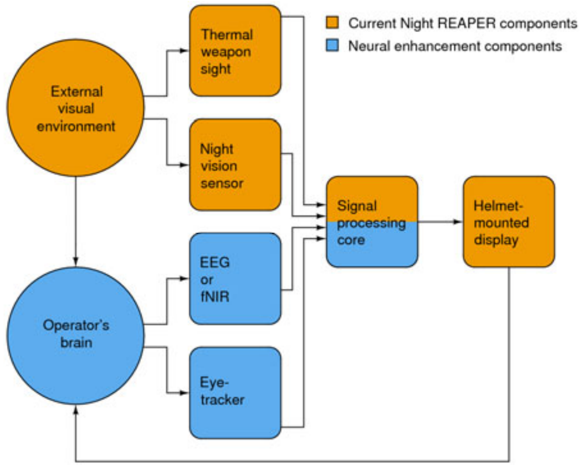

Fig. 3. Block diagram of proposed system, depicting current Night REAPER components (orange) and components required for a neural interface (blue)

2.2 Potential Neural Enhancements

Neural enhancements of the Night REAPER system can generally be divided into two categories—system management and brain-assisted sensory processing. System management generally encompasses the management of the augmented reality system with user-generated brain activity. This could include the switching of visualization modes (e.g., from helmet-mounted, intensified night vision to TWS). Brain-assisted sensory processing entails employing the user's brain to perform sensory processing tasks that are generally challenging for computer systems. This may include detection of novel objects in the environment, classifying a vehicle target, or tracking a target as it moves through the scene.

2.3 Constraints on the Neural Interface

Dismounted warfighter platforms are subject to strict size, weight, and power restrictions. For example, the total weight of helmet-mounted, body-worn and weapon-mounted components must be minimized because dismounted warfighters already carry more than 50 pounds of gear, which can limit their mobility [3]. The helmet-mounted weight is limited to 1.5–2 pounds, a requirement that arises from the fact that a combat helmet typically weighs 3–3.5 pounds [8], and guidelines intended to limit neck injury dictate that total head-supported weight not exceed 5 pounds [7]. The incorporation of a brain-machine interface (BMI) into such a system poses a unique set of challenges; in many cases, BMI research has assumed unlimited computing resources and an inexhaustible power supply. Furthermore, the sensors that transduce the neural signals must be integrated with a combat helmet while preserving the helmet's ballistic protection.

The power consumption requirements of the neural interface are indirectly dictated by the body-worn weight requirement—the user must carry enough batteries to supply the system for a typical three-day mission. This translates to 8 hours of operation on a single set of batteries, which imposes a tight constraint on power consumption.

The latency requirements of the neural interface are dictated by the nature of the task the user is performing. For system management tasks like mode selection, the time between when the user thinks the command and the change in mode should be comparable to a conventional button-press method. The latency requirement for brain-assisted sensory processing is highly task-dependent, ranging from hundreds of milliseconds for novelty detection, to seconds for a more challenging task.

3 Neural Interface for the Night REAPER System

The neural interface is shown in the context of the entire system in Figure 3. It can be further broken down into lower-level blocks, as shown in Figure 4. Brain activity is recorded by one or more sets of sensors, and then decoded into a form that the user interface control can understand. The user interface control then updates the HMD.

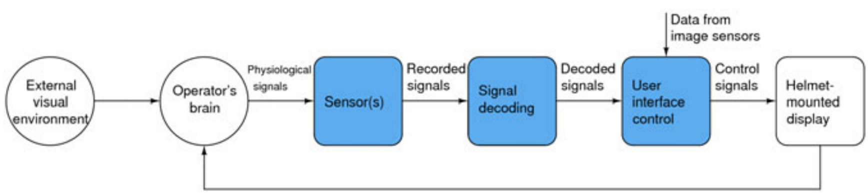

Fig. 4. Block diagram of neural interface to sensory augmentation system. Neural interface components are highlighted in blue.

3.1 Signals

A critical aspect of the proposed system is its reliance on intuitive neural control signals that do not require the user to shift their attention from the task at hand. The vast majority of studies on BMI to date have relied upon "artificial" strategies for neuromodulation that require significant mental effort, such as performing motor imagery tasks or mental calculations, but there are a few reports in the literature of BMI systems that operate on naturally occurring neural signals (reviewed in [1]). The ability to decode such signals is critical for system acceptance; a BMI that requires attention to be directed away from the mission would likely add to the user's cognitive burden, as opposed to relieving it.

3.2 Sensors

Many sensors have been considered for BMI, including electroencephalography (EEG), functional near infrared (fNIR) imaging, functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and implanted microarrays [4]. The size, weight, and power constraints outlined above limit the types of neural acquisition systems that can be used by the system. For example, fMRI and MEG require room-sized sensors and controls that are by no means portable, and implanted microelectrodes are not reliable enough to be incorporated into non-medical fieldable systems. Consequently, in the near term, EEG and fNIR are the most likely candidates for sensors that can be straightforwardly integrated with a combat helmet.

The choice of EEG versus fNIR affects some system requirements but not others. For example, both EEG and fast optical signal (FOS)-based fNIR have similar bandwidth and sample rate requirements, as the FOS appears to directly reflect aggregated neural spike activity in real-time and can be used as a high-bandwidth signal akin to EEG [6]. However, EEG and fNIR will have differing effects on other system parameters such as the physical interface to the human user and the size, weight and power budget. The physical interface in particular merits scrutiny, as it is non-trivial to maintain a good connection between an electrode/optode and the scalp in freely-moving users. Active EEG electrodes help to eliminate movement artifacts, but the best EEG recordings are typically derived from preparations in which the scalp is abraded and contact is made through conductive gel. Neither of these considerations is easy to employ in a fieldable neural interface technology, but this problem has recently received much attention from the military and may be solved with novel electrode technologies in the near future [2]. In contrast to EEG, the use of fNIR eliminates motion artifacts and the need for both scalp abrasion and conductive gel, but introduces a problem of a low signal-to-noise ratio when considering the FOS.

3.3 Decoding

Due to the diversity of neural interfaces and BMI applications, there is no “standard” approach to decoding neural control signals [1]. Moreover, the specific decoding algorithm employed will depend heavily on the operational paradigm. For example, a decoder that runs in continuous time may look for unique spatiotemporal patterns in the multi-channel neural data, or simply watch for modulation of signal power in one or more frequency bands. Alternatively, if the decoder is queued to operate during intervals in which the user must choose between a finite number of options, event-related decoding strategies can be employed to identify event-related synchronization or desynchronization, or event-related potentials. Steady-state visual evoked potentials could also potentially be used if the selection alternatives are presented at different temporal intervals.

For any choice of decoding algorithm, there is a large spectrum of possible inputs to the algorithm. For example, some algorithms operate on the raw waveforms from one or more channels of recording, while others require data preprocessing to extract salient features such as signal power within a particular frequency band, or a projection of the raw data into a lower- or higher-dimensional subspace [1]. In some cases, features can be selected based on empirical or theoretical models of the expected neural response—a classic example is found in systems relying on event-related potentials such as the visual P300 signal, which typically employ a matched filter with a peak at 300 milliseconds post-stimulus [5]. However, it is more often the case that there is no underlying model for the expected neural activity, so a broad range of features is empirically evaluated through either manual or automated searches.

Statistical machine learning techniques can be employed to identify patterns in the inputs. Previous BMI research and development efforts have demonstrated the utility of a diversity of techniques including neural networks, linear discriminant analysis, Bayesian approaches, support vector machines (SVM), Kalman filters, and random forests [1]. As with the input features, there is often no principled way to ascertain which technique will be most effective on any particular dataset, so multiple alternatives should be evaluated and compared for both accuracy and efficiency.

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