Augmented Human: Human OS for Improved Mental Function (Position Paper)

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Abstract

This position paper summarizes some of our initial work, as well as future research opportunities, in the area of augmenting human mental functioning via a real-time analysis of various measurements reflecting person's physiological and mental states. EEG, heart rate, blood pressure, and galvanic skin response, among several other measurements, can be collected using cheap wearable devices that are currently available on the market; moreover, novel devices that are still under development, such as electronic tattoos, promise further increase of the measurement quality, ease of use, and, as a result, even wider adoption of wearable technologies in the near future. Also, more traditional measurements of human behavior, such as speech and text, collected from various mobile devices (for example, smart phones), can be combined with the data collected by wearable devices in order to produce a more accurate inference of a person's mind state and behavior. We briefly describe a working demo in the context of a case study system that uses an EEG signal from a subject driving a car. We envision detecting both situations in which the operator may be a danger to the system, as well as occasions when the system may be a danger to the operator. Based on an Android phone and a low-cost NeuroSky EEG device, we explore applications to improve road safety. We also review existing work focused on interruptions during certain activities, as well as speech and text analysis, that can be combined with physiological data to accurately classify a person's mental state and make better decisions about when interruptions (such as, for example, an incoming phone call when the driver is in the middle of changing lanes or merging on a busy highway) would be particularly dangerous.

Introduction

"The driver of a New York commuter train that derailed at high speed last year, killing four people, had a serious sleep disorder that interrupted his rest dozens of times each night" (The Guardian, 4/7/14). "The driver of a train that jumped the tracks last month at Chicago O'Hare International Airport – after having reportedly "dozed off" – has been fired" (CNN, 4/5/14). Previous research has shown that micro sleeps and drowsy behavior due to obstructive sleep apnea syndrome (OSAS) are easily detectable using off-the-shelf EEG equipment (Boyle et al. 2008). Also, the mild cognitive decline typically associated with an advanced age of a driver (note that older drivers are over-represented in crash statistics (Evans 2004)) has been characterized by on-road evaluation techniques (Lees et al. 2010). These are just two examples of detecting humans in a state that puts a system (and humans) at risk. The CDC estimates[1] suggest that, in the United States, each day more than 9 people are killed and more than 1,060 people are injured in crashes reported to involve a distracted driver. Distracted drivers are an example of both a system posing a danger to a human and a human being in a state that poses a danger to the system. Our ultimate objective is to identify and preempt situations when a human mental state is posing a danger, as well as to eliminate or defer electronic interactions when they would pose a danger. There is already some prior work on quantifying cognitive states (Fadlallah et al. 2012) and classifying mental or cognitive load based on EEG data, as well as on deferring interruptions or otherwise adapting to the subject's state (Chen and Vertegaal 2004; Mathan et al. 2007; Antonenko et al. 2010). Our goal is to advance the state-of-art in this are by combining as many data sources as possible, including both human and environmental sources (light, sound level, location, temperature, humidity), to allow for further discovery of phenomenology and correlations among the mental states and behavior. A model of the mental state of the subject would be available to applications that could then adapt their behavior to their user's mental state.

Examples of application in other situations include identifying particularly ill-designed and difficult-to-use software. Users tend to grow annoyed and irritated by factors such as poor design, broken links, slow response time, not-so-intuitive user interface, unnecessary complexity, timing and content of messages. Many pieces of software seem to be coded with the assumption that interrupting the user at any time is completely acceptable. Prompts to download updates, purchase the newest version, announce the status of the latest security scan can be very disruptive to productivity of a user. If user's aggravation could be quantified and

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[1]http://www.cdc.gov/motorvehiclesafety/distracted_driving/

communicated to the software owners, or if a ranking of the most annoying software could be produced, and an indication of when interruptions might be acceptable existed, then this type of interruptive behavior might be mitigated.

One final scenario in which mental state characterization could be useful is awareness of self and others in social situations. Sensitive software can detect impatience, agitation, excitement and/or other emotional changes and alert you to the fact that you may need to relax or adapt your presentation/explanations/etc. to the characteristics of a particular audience. Immediate feedback to the user as well as data collected over time could then be used to guide behavior and quantify progress.

The scenarios above are quite realistic, given real-time access to the subject's physiological data measured by existing wearable devices. Simple, low-cost EEG devices (e.g., NeuroSky Mindwave) can capture signals indicative of attention and relaxation levels, and will be used in our demo discussed below. Other relevant measurements would be heart rate variability (HRV) and galvanic skin response (GSR), known to be correlated with the level of stress. For example, there are several patents (e.g., see (Eggenberger, Malkin, and Sorenson 2012)) covering the use of HRV for analyzing physical and emotional states of employees performing different tasks in a workplace.

There is also a rapidly growing body of work on recognizing mental states from other types of input, such as text, speech, video, etc. For example, (Mota et al. 2012) present a text-analysis approach based on syntactic graphs and their topological properties, that allows for a very accurate (above 90%) classification of mental disorders such as bipolar disorder and schizophrenia, from relatively short interviews with patients; Figure 1, reproduced here from the above paper, provides an example of syntactic graphs constructed from several interviews, clearly illustrating differences between the control, schizophrenic and manic subjects. Another recent work, by (Bedi et al. 2014), in the area of text-analytic approaches for psychiatric applications, studies speech alteration effects of psychoactive drugs and demonstrates how an automated semantic speech analyses can capture subtle alterations in mental state, accurately discriminating between the effects of different drugs. The findings also illustrate the potential for automated speech-based approaches to characterize clinically-relevant alterations to mental state, including those occurring in psychiatric illness. Yet another recent work uses speech, focusing only on acoustic features, in order to accurately discriminate between elderly controls versus the same-age patients with mild cognitive impairment (MCI) and Alzheimer's disease (Satt et al. 2013). Note, that while the above examples are in the context of mental disorders, we hypothesize that similar approaches can be used to detect mental states and their changes in normal subjects as well. For example, a person feeling very tired and/or depressed may start using shorter sentences; an excited (or intoxicated) person, vice versa, may become more talkative than usual, with increased repetitions of words related to the topic of excitement, and so on.

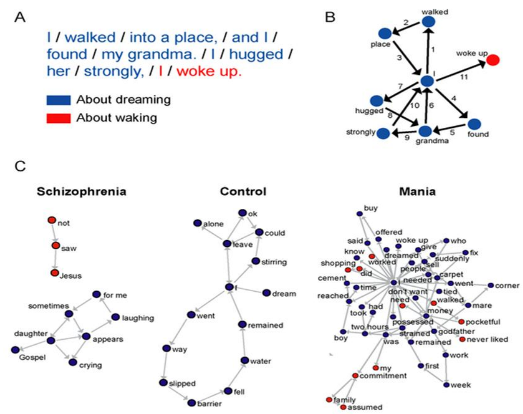

Figure 1: Syntactic graphs computed from interviews with subjects: (a) and (b) illustrate graph construction from the text: nodes correspond to words/concepts, while directed links represent word sequence in a sentence; (c) examples of graphs for three types of subjects – note clear differences between the graph topologies when comparing control (middle), schizophrenic (left) and manic (right) subjects.

Human Operating System

As cited above, there have been many successful proof-of-concept projects related to collecting, analyzing and modeling human cognitive states. However, software sensitive to human mental states is not in common use, with the possible exception of gaming applications. We feel that novel environments are needed, that enable the path from the mental-state insensitive to mental-state sensitive applications, and from an individual vertical silo to a collective assessment and exploitation. For these reasons, we propose a core set of *Human Operating System (Human OS)* services to create an environment that provides access to mental-state related data sources, abstracts low-level metrics, and makes code portable across devices. Mobile phones have many advantages for such a platform. They are currently multicore and powerful enough to accommodate data collection and analysis. They have sensors for location, motion, sound, light, and access to text and voice communication. They can use Bluetooth communication to interface with external sensors for bioelectrics (EEG, EMG, EOG, GSR, HRV) and environmental factors, such as carbon monoxide (CO) and volatile organic compound (VOC) levels. They are in widespread use and usually in close physical proximity to their owners. They are connected to the internet and their operating systems provide powerful services such as speech to text, access to off device storage such as Google Drive and internal SQL databases. The data services in our project handle low-level device communication such as Bluetooth and interact with location services and native phone sensors. Low-level metrics are abstracted to higher level concepts (sleepy, manic, depressed, focused, etc.), which are then portable across device types and sensors. Access to the time series data, as well as current values of the metrics collected in real-time enables both time-series analytics, as well as short-term control functions.

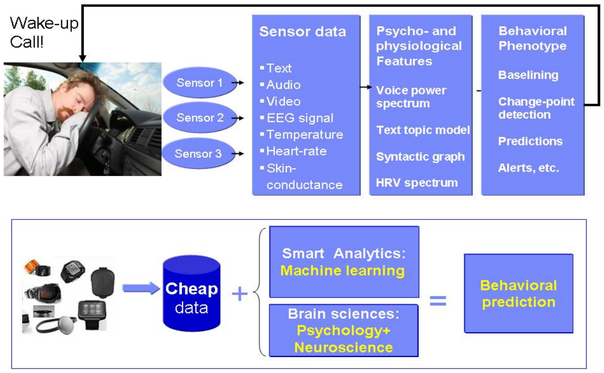

Figure 2: Human operating system: collecting and analyzing personal data from cheap wearable devices and other "easy" sources of information, and providing feedback in real time.

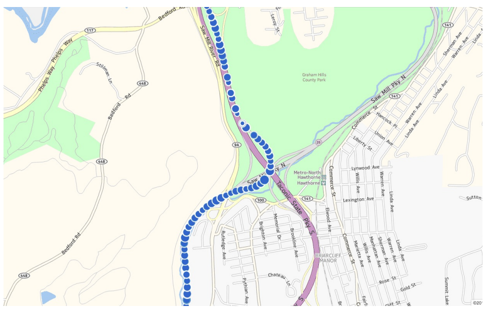

Figure 3: Mental State aware software can defer interruptions when extra concentration is necessary such as merging shown above. Size of blue dots is proportional to relaxation index. Note greater relaxation waiting at stop light and less when merging onto highway. Interruptions when merging should be deferred, interruptions while stuck in traffic might be OK.

Note that a typical OS service is resource allocation. In our case, one of the scarce resources that needs to be allocated is human attention and cognitive capacity. By making inference about the subject's mental state, applications can deliver cues and prompts. If the subject is sleepy and driving, then a break, or driver switch, or other mitigation can be suggested. Interruptions can be deferred if the subject is in a flow state. Having the ability to off-load data allows for archiving and training models on longitudinal data. The ability to combine abstracted sensor data with the inference based on multi-dimensional human mental-state models allows for a holistic view of the subject in an environment where action can be taken at the decisive moment. See Figure 2 for a high-level summary of the idea outlined above.

An example illustrating our case study of driving behavior using the Human OS is presented below. A subject (in this experiment, one of the co-authors of this paper) wore a NeuroSky EEG device while driving to work. The device connects via Bluetooth to an Android phone in the car. The device provides a proprietary attention and relaxation index, as well as raw EEG waveform from which frequency band

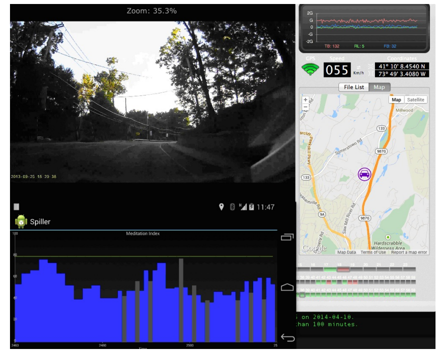

Figure 4: A screenshot of the demo: example of integrated camera, location, EEG application. Looking for phenomenology and correlation of mental state to driving conditions and situations.

power is extracted. On the display for immediate feedback to the subject is the relaxation index (higher bars are indicative of a more relaxed state). The Human OS Android application allows the subject to speak and annotate the data tracks with event information. All data tracks are available in real time and after a session a CSV file can be transferred to Google Drive. Power in different frequency bands is generally recognized to be associated with the following states: beta (15-30Hz) corresponds to fast, awake state, normal alert consciousness; alpha (9-14 Hz) is associated with normal relaxed state in adults with eyes closed and relaxed; theta (4-8 Hz) corresponds to slow activity common in children and abnormal in awake adults; finally, delta (1-3 Hz) is common in infants, as well as in stages 3 and 4 of sleep[2]. Many studies quantifying meditation states using EEG measures have been done over the years, providing techniques for classification (Cahn and Polich 2006; Lutz et al. 2004). One study that is facilitated with our setup is the effect of conscious relaxation while driving. An interesting question is whether it is possible to cultivate a state that is the opposite of what is commonly known as 'road rage'. The EEG data is recorded along with location, time, sound level, and light level. The screen of the phone can also be recorded and played back, registered with dashcam footage and the vehicle position on the map to look for phenomenology.

In this particular scenario, the relaxation index was also plotted on a static map in Figure 3, where the radius of a circle is proportional to the relaxation level. Some basic effects are readily apparent. Relaxation inversely correlates with speed. Being completely stopped at a traffic light was associated with a higher relaxation level. The moment of decision about whether to merge on to the highway or to wait for traffic was less relaxing. That would clearly be a bad time to interrupt the driver. If the subject took the same route every day, it would be possible to predict places where extra concentration was needed. Alternatively, with data from many subjects it might be possible to populate the map with concentration hotspots, in order to model a naive subject's

[2] http://www.medicine.mcgill.ca/physio/vlab/biomed_signals/eeg_n.htm

experience on an unfamiliar route. Using this information would allow for a better interruption management. Also, it would be interesting to analyze correlations with such "environmental variables" as intersections, bad surface conditions, pedestrians, adverse weather conditions such as snow, fog, or sun glare, aggressive drivers, slow moving traffic, accidents, and police activity. The legal status of mobile phone and in-car screen use in the US is fragmented[3]. While the authors feel that cell phone use in cars is dangerous in general, as long as it is legal in some jurisdictions, it makes sense to attempt to make it as safe as possible. One research direction is to characterize driver versus passenger, in order to allow passengers to use their phones but restrict the phone usage by drivers. Voluntary solutions proposed by wireless carriers[4] have not been widely embraced, and thus a technical solution may be necessary in the absence of broad laws and effective law enforcement.

Figure 4 presents a screenshot of our demo system, displaying the drivers view via video recording, the map, and the EEG derived relaxation level.

Discussion and Future Directions

As smart phone and wearable device sensors have become ubiquitous, there has been a rapid progression along the lines of detecting physical, emotional and cognitive states of humans. In addition to the related work on text and speech analysis for mental state detection, there is considerable amount of work attempting to characterize human emotions from video[5]; detecting mental states from wearable EEG devices[6], such as ones made by Emotiv and NeuroSky; detecting fatigue level using actigraphy (objective measure of activity and sleep/wake patterns over time) using devices such as Actiwatch[7]; tracking activity and health meters (e.g., heart rate, GSR, etc) using wrist devices such as Basis watch [8], Fitbit and many others[9]. Future developments in wearable devices are expected to be in the direction of making such devices smaller, more comfortable and easier to wear and use; one particularly interesting example is electronic tatoos[10].

Recently developed wearable sensor technology opens new opportunities for real-time monitoring of human health and behavior, with multiple potential advantages, including interruption management, accident prevention, workplace productivity improvement, better personal health, and improved cognitive and social skills. Integration of multimodal personal data along with environmental data collected from multiple devices and real-time statistical analysis, including predictive modeling, change-point detection, unsupervised feature extraction, transfer learning (between the subjects, and between activities), and other machine-learning capabilities, will become essential parts of what we call the Human Operating System. This system will complement and augment (rather than interfere with or interrupt) human mental abilities, in order to achieve an "augmented human". Moreover, this type of a mental-state-aware system, that feeds cues and prompts to the users in harmony with their condition, seems to be a natural fit for an augmented reality tools such as Google Glass.

[3] http://www.ncsl.org/research/transportation/cellular-phone-use-and-texting-while-driving-laws.aspx

[4] http://www.nytimes.com/2012/09/20/technology/att-chief-speaks-out-on-texting-while-driving.html?_r=0

[5] See, for example, http://well.blogs.nytimes.com/2014/04/28/reading-pain-in-a-human-face/

[6] See http://mobihealthnews.com/24401/nine-health-wearables-for-your-head/

[7] http://www.bmedical.com.au/shop/fatigue-heat-stress.htm

[8] http://gigaom.com/2012/11/29/more-than-an-activity-monitor-basis-watch-wants-to-change-your-life/

[9] http://www.pcmag.com/article2/0,2817,2404445,00.asp

[10] http://www.physicscentral.com/explore/action/tattoos.cfm

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