Sensitive, Diagnostic and Multifaceted Mental Workload Classifier (PHYSIOPRINT)

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Abstract. Mental workload is difficult to quantify because it results from an interplay of the objective task load, ambient and internal distractions, capacity of mental resources, and strategy of their utilization. Furthermore, different types of mental resources are mobilized to a different degree in different tasks even if their perceived difficulty is the same. Thus, an ideal mental workload measure needs to quantify the degree of utilization of different mental resources in addition to providing a single global workload measure. Here we present a novel assessment tool (called PHYSIOPRINT) that derives workload measures in real time from multiple physiological signals (EEG, ECG, EOG, EMG). PHYSIOPRINT is modeled after the theoretical IMPRINT workload model developed by the US Army that recognizes seven different workload types: auditory, visual, cognitive, speech, tactile, fine motor and gross motor workload. Preliminary investigation on 25 healthy volunteers proved feasibility of the concept and defined the high level system architecture. The classifier was trained on the EEG and ECG data acquired during tasks chosen to represent the key anchors on the respective seven workload scales. The trained model was then validated on realistic driving simulator. The classification accuracy was 88.7 % for speech, 86.6 % for fine motor, 89.3 % for gross motor, 75.8 % for auditory, 76.7 % for visual, and 72.5 % for cognitive workload. By August of 2015, an extended validation of the model will be completed on over 100 volunteers in realistically simulated environments (driving and flight simulator), as well as in a real military-relevant environment (fully instrumented HMMWV).

Keywords: Mental workload · Assessment · EEG · IMPRINT · Wearable

1 Introduction

The construct of mental workload – defined as the degree to which mental resources are consumed by the task at hand - is difficult to quantify. This is due largely to the nature of the construct, a latent or hidden variable that results from an interplay of several other variables such as the objective task load, external distractions (task-irrelevant stimuli that draw one's attention and temporarily occupy mental resources), internal

D.D. Schmorrow and C.M. Fidopiastis (Eds.): AC 2015, LNAI 9183, pp. 101–111, 2015.
DOI: 10.1007/978-3-319-20816-9_11

distractions (e.g. task-related stress, task-irrelevant mentation), capacity of one's mental resources and strategy of their utilization (Fig. 1). The overall capacity of mental resources and strategy of allocating them to the tasks are, in turn, strongly dependent on individual traits (e.g. personality profile, stress resiliency), previous training and factors such as motivation, fatigue and stress. Furthermore, for any given individual, different types of mental resources such as attention, audio-visual perception, cognition or motor control will be mobilized to a different degree in different tasks even though the subjective perception of their 'difficulty' may be the same [1, 2]. An ideal measure of mental workload therefore needs to be multifaceted and diagnostic, such that is had the ability to quantify the engagement levels of each of mental resources before eventually combining them into a single global measure. Moreover, it should be able to model the impact of individual traits and psychophysiological states onto the capacity and utilization of mental resources to a degree that does not hamper its ease of use.

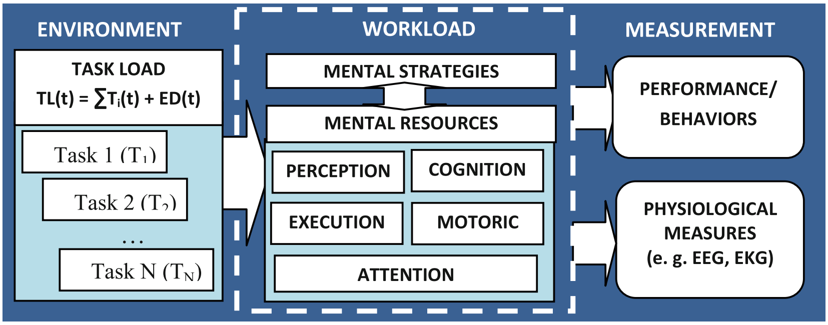

Fig. 1. Schematic presentation of the concept of mental workload and its relationship with pertinent variables: task load (TL), capacity and management of mental resources (MR, MS), individual traits and states (e.g. fatigue), and external and internal distractions (ED and ID).

The standard techniques for workload assessment include self-report scales, performance-based metrics, and physiological measures. Self-report scales are popular due to their low cost and consistency (assuming that the individual is cooperative and capable of introspection). Some of these scales are one-dimensional such as the Rating Scale of Mental Effort (RMSE) and the Modified Cooper-Harper scale (MHC) [3], whereas some scales comprise subscales that measure specific mental resources, e.g., NASA Task Load Index (TLX) [6], Subjective Workload Assessment Technique (SWAT) [5], and Visual Auditory Cognitive Psychomotor method (VACP) [4]. The major drawback of these measures is that they cannot be unobtrusively administered during the task, but are assessed retrospectively at its conclusion. Furthermore, the inherent subjectivity of self-ratings makes across-subjects comparisons difficult. Self-report scales are, therefore, often complemented with performance measures, such as reaction time to different events or accuracy of responses. The performance assessment is relatively unobtrusive and can be accomplished in real time at low cost, but it is not sensitive enough because of the complex relationship between the two variables [7, 8]. Moreover, performance measures cannot tap into all cognitive resources with comparable accuracy. Lately, there has been renewed interest in physiological measures as workload assessment metrics, and signals [9–16] such as electro-oculography (EOG), electromyography (EMG), pupil diameter, electrocardiography, respiration, electroencephalography and skin conductance. Until recently, their utility was limited by the obtrusive nature of earlier instrumentation, but this has changed with the advent of miniaturized sensors and embedded platforms capable of supporting complex signal processing techniques. Still, physiological workload measures have multiple drawbacks. First, the physiological workload scales are often derived empirically on a set of tasks assumed to represent different workload levels and selected ad hoc, without detailed consideration of their ecological validity and ability to tap into different mental resources (e.g., cognitive, visual, auditory, or motor workload). As a result, the models trained on such atomic tasks may not perform well when applied to the physiological signals acquired during other non-atomic tasks even though they seemingly require the same mental resources. Second, in spite of the well known fact of considerable between- and within-subject variability of nearly all physiological signals and metrics, the majority of physiological workload models have been developed and validated on a relatively small sample of subjects. Third, the classifiers used in the models introduced hitherto have typically lacked mechanisms for an adjustment of the model's parameters in relation to individual traits, which leads to models that do not generalize well. Finally, the models have mostly ignored the considerable amount of noise inherent in the acquired physiological signals. Thus, poor performance of some models could be attributed to their reliance on rather simple mathematical apparatus.

This paper introduces PHYSIOPRINT - a workload assessment tool based on physiological measures that is built around an established theoretical model called Improved Performance Research Integration Tool (IMPRINT) [17]. The proposed model distinguishes among seven different workload types, and is trained on tasks chosen to represent the key anchors on the respective workload scales. Its mathematical apparatus is not computationally expensive, so it is applicable in real time on a fine timescale.

The rest of the paper is organized as follows. In Sect. 2 we outline the experimental setting while Sect. 3 reports on the experimental results. Finally, in Sect. 4, we summarize our results and give an outlook on future work.

2 Methods

2.1 IMPRINT Workload Model

The IMPRINT Workload Model, developed by the Army Research Laboratory (ARL) [17], discriminates between seven types of workload: visual, auditory, cognitive, fine motor, gross motor, speech, and tactile. Each workload type is quantified on an ordinal/interval scale, similar to the VACP scales [4]. Each of the seven scales is defined by a set of behaviors of increasing complexity that are associated with a numeric value between 0 and 7. Furthermore, for each point in time, IMPRINT produces a composite measure of the overall workload, which is defined as a weighted sum of the type-specific workload values calculated across all tasks that are being simultaneously performed. The model has been successfully applied to estimate mental workload in a number of settings of military relevance, including a strike fighter jet, a mounted combat system [18], and the Abrams tank [19].

2.2 Study Design

Twenty-two healthy subjects (11 females, 25 ± 3 years) who had reported no significant previous or existing health problems participated in the study. They were required to maintain a sleep diary for 5 days prior, and refrain from alcoholic and caffeinated beverages 24 h prior to the experiment. The experiment would typically start at 9AM, when the attending technician would set up the subject with the sensors and recording equipment (Figs. 2 and 3). The wireless X24 sensor headset (Advanced Brain Monitoring Inc., Carlsbad, CA, USA) was used to acquire 20 channels of electroencephalography (EEG) along with electrocardiography (ECG), respiration and head movement data, while a smaller X4 device from the same manufacturer recorded the forearm electromyography (EMG). Following the setup, the subject would engage in a series of computer-based auditory, visual, cognitive and memory tasks that corresponded to the key anchors of the respective workload scales from the IMPRINT model (*atom tasks*, Table 1). The subject would next perform a set of physical exercises on a treadmill (3 min of walking at 2 mph at 0° inclination, 3 min of running at 6 mph at 0° inclination, 3 min of walking at 2 mph at 15° inclination, 3 min of walking at 6 mph at 15° inclination) and with weights (lift-ups with 5–10 lb in each hand). The subject would then participate in a 30 min session in a driving simulator, and, finally, repeat the computer-based atom tasks. The entire session was recorded with a microphone and video camera that were mounted on the PC or treadmill displays in front of the participant. The protocol was approved by a local Institutional Review Board; all subjects signed an informed consent before the experiment began, and were financially compensated for their participation in the study.

Setup (30 min)	Atom tasks (90 min)	Exercises (15 min)	Driving tasks (30 min)	Atom tasks (90 min)

Fig. 2. Sequence of experimental activities and their estimated duration

2.3 Data Processing and Analyses

All computerized tasks, physical exercises and driving scenarios were scored on a second-by-second basis with respect to the workload they impose in accord with the IMPRINT workload model [17, 18]. Each EEG channel was processed with proprietary algorithms to eliminate artifacts and derive spectral features for each subsequent 2-s data segment with 1 s (50 %) overlap. ECG signals was filtered, QRS complexes were detected, and beat-to-beat heart rate (HR) were converted into second-by-second values. Time- and frequency-domain measures of heart-rate variability (HRV) were derived from the HR data in accord with the literature [20]. EOG signals were

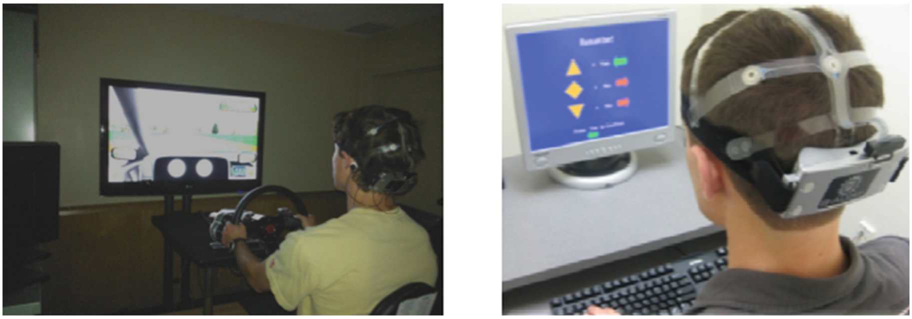

Fig. 3. A subject during a driving simulator task (left) and computer-based atom tasks (right)

processed with our proprietary algorithms for detection for eye blinks and eye fixations. EMG levels and body and limb motion were quantified in each second of the data using the bin integration. In addition to these 'absolute' or primary variables, a number of secondary or 'relative' variables were derived by computing ratios and/or differences between different time instances of the same primary variable or between different but functionally or spatially related primary variables (e.g. anterior-posterior gradient of the alpha EEG power). Finally, brain-state variables quantifying fatigue, alertness and distraction were derived using our validated classifiers [15, 16]. Step-wise regression analysis was used to identify variables derived from the physiological signals that are most predictive of the IMPRINT workload profiles and performance. The analyses took into account the existing relationship between specific workload types and certain physiological signals (e.g. speech workload scale and respiration, gross motor workload and heart rate or body/limb motion).

3 Results

3.1 Speech Workload Scale

The impedance-based respiration signal and sound envelope from our X12 device sufficed for a very precise identification of speech episodes across the pertinent tasks (A2, A4, C3, C4, S1 and S2). Between-subject variability was not significant, and overall classification accuracy amounted to 88.7 % (Table 2).

3.2 Fine Motor Workload Scale

The EMG acquired from the forearm was a good source for identification of fine motor activities in the pertinent tasks (B4, B5, C1, C2, A1, F1). Between-subject variability was relatively large, and normalization with respect to the baseline EMG activity (defined as the EMG activity during tasks B1 and B2) was required for obtaining the classification accuracy of 86.6 % (Table 3). As one can observe, the sensitivity was high for no activity and short discrete activities (on/off EMG pattern), but there was

Table 1. Low workload PHYSIOPRINT tasks

Task	Description
B1 3min	A brief tone (500ms, 40dB) is played through the earphones every 5 seconds; the participant keeps the eyes closed; no response to the stimulation is required.
B2 3 min	A brief tone (500ms, 40dB) is played through the earphones every 5 seconds; the subject looks at a blank screen; no response to the stimulation is required.
B3 3 min	A brief tone (500ms, 40dB) is played through the earphones every 5s; concurrently, 2 images are shown on a screen as a distraction; no response required.
B4 3 min	A brief tone (500ms, 40dB) is played every 5s; the subject looks at a blank screen; a button press is required in response to each stimulus.
B5 3 min	A brief tone (500ms, 40dB) is played every 5 seconds; concurrently, two images are shown on a screen; a button press is required in response to each stimulus.
V1 3 min	Every 5s a pair of images is shown on the screen, and the subject is asked to communicate if the images are associated.
V2 3 min	Every 5s a pair of images with virtual knobs is displayed: one in a neutral, the other in a target position. The subject uses a real knob to align the two.
V3 5 min	Every 10s 9 objects appear in the left half of the screen, then drift to the right half via pseudo-random paths. The subject is expected to track 1-3 of them
V4 3 min	Every 5s two completely or nearly identical images are shown on the screen; the participant is expected to find the difference, if it exists.
V5 3 min	Every 5s a complex image and a simple image (object) are displayed; the subject is expected to find/locate the displayed objects within the complex image.
A1 3 min	Every 5s a brief tone is played to one (20%) or both ears (80% of the cases); a key press is required in response to the unilateral tone.
A2 5 min	Every 5s a verbal command is issued; a response requested by the command is expected (eye blink, button press, verbal response, body position change)
A3 3 min	The participant uses a joystick (held in the dominant hand) to balance (i.e. cancel out) the sound levels in the left and right ears
A4 5 min	A combination of A1 and A2: tones OR commands delivered every 5s, a differential response is required (key press for unilateral tone, or as instructed)
C1 3 min	Every 20 seconds a sequence of 3-9 digits is displayed (1 digit/s). The subject is expected to type them into a text box after a variable pause period (1-10s)
C2 3 min	Every 20 seconds a sequence of 3-9 digits is read aloud (1 digit/s). The subject is expected to type them into a text box after a variable pause period (1-10s)
C3 3 min	Every 20 seconds a sequence of 3-9 digits is displayed (1 digit/s). The subject is expected to reproduce them verbally after a variable pause period (1-10s)
C4 3 min	Every 20 seconds a sequence of 3-9 digits is read aloud (1 digit/s). The subject is expected to reproduce them verbally after a variable pause period (1-10s).
C5 3 min	Every 20s the participant is shown an arithmetic problem on the screen (addition, subtraction, multiplication or division). The response is typed in.
S1 3 min	Every 5s a command is shown on the screen: to hold his breath, keep breathing normally, or read aloud a brief (<3 words) or a long (up to 8 words) sentence.
Task	**Description**
S2 3 min	Same as S1, except that the subject may also be instructed to repeat (say aloud) the last sentence that has been displayed on the screen
F1 3 min	Every 5s various a contour of an object is shown on the screen of a tablet; the participant uses a stylus to track the contour.

Table 2. Classification of speech events

	BEHAVIORS			
CLASSIFIED AS	**Breath hold**	**Normal breathing**	**Short speech (<5s)**	**Long speech (>5s)**
Breath hold	1946	33	43	23
Normal breathing	59	1928	77	79
Short speech (<5s)	105	127	2591	272
Long speech (>5s)	0	24	215	1911
TOTAL	2110	2112	2926	2285
Sensitivity (SE)	92.2%	91.3%	88.6%	83.6%
PPV	95.1%	89.9%	83.7%	87.4%

Table 3. Classification of fine motor events

	BEHAVIORS				
CLASSIFIED AS	**None**	**Discrete actuation (key press)**	**Keyboard typing**	**Contour tracking**	**Continuous adjustment**
No activity	6902	73	2	0	15
Key press	337	4896	176	0	112
Keyboard typing	374	507	863	12	120
Contour tracking	402	67	6	1193	995
Driving	76	59	4	379	3056
TOTAL	8091	5602	1051	1584	4298
Sensitivity (SE)	85.3%	87.4%	82.1%	75.3%	71.1%
PPV	98.7%	88.6%	63.1%	44.8%	85.5%

more confusion between the continuous activities (steering wheel adjustments vs. contour tracking).

3.3 Gross Motor Workload Scale

The X-, Y-, and Z-axis signals from the accelerometer within our head-worn EEG recorder and arm-worn peripheral recorder proved to be an excellent source for differentiation of gross motor activities (push-ups and treadmill exercises). Between-subject variability was not significant, and the classification accuracy reached 89.3 % (Table 4).

3.4 Auditory Workload Scale

The classifier attempted to distinguish among 5 conditions: ‘no activity’ (silent breaks during tasks B1–B3), register a sound (beeps delivered throughout tasks B1–B5), ‘discriminate sounds’ (uni- vs. bilateral beeps in tasks A1 and A4), ‘interpret speech’

Table 4. Classification of gross motor events

	BEHAVIORS			
CLASSIFIED AS	**Sitting**	**Walking**	**Running**	**Push-ups**
Sitting	2992	13	9	2
Walking	68	5554	379	198
Running	0	272	5628	228
Push-ups	93	473	293	2720
TOTAL	3153	6312	6309	3148
Sensitivity (SE)	94.9%	88.0%	89.2%	86.4%
PPV	99.2%	89.6%	91.8%	76.0%

Table 5. Classification of auditory events

	CONDITIONS				
CLASSIFIED AS	**No activity**	**Register a sound**	**Discriminat e sounds**	**Interpret speech**	**Interpret pattern**
No activity	7097	2334	28	56	59
Register a sound	1874	8938	72	63	67
Discriminate sound	275	147	2194	119	103
Interpret speech	113	49	383	6465	322
Interpret patterns	79	125	385	1738	1576
TOTAL	9438	11593	3062	8441	2107
Sensitivity (SE)	75.2%	77.1%	71.6%	76.6%	74.8%
PPV	74.1%	81.1%	77.3%	88.2%	40.4%

(digits read during tasks C2 and C4), and interpret sound patterns (different honking patterns during the driving task). The overall classification accuracy (shown for a classifier developed on combination of subsets of feature vectors from both times of the day) amounted to 75.8 % (Table 5).

3.5 Visual Workload Scale

The classifier attempted to distinguish among 5 conditions: ‘no activity’ (silent breaks during tasks B1–B3), register an image (tasks B4, B5), ‘detect a difference’ (task V4), ‘read a symbol’ (digits read during tasks C1 and C3), and scan/search (task V5). The overall classification accuracy (shown again for a classifier developed on combination of subsets of feature vectors from both times of the day) amounted to 76.7 % (Table 6).

3.6 Cognitive Workload Scale

The classifier attempted to distinguish among four (4) conditions: ‘no activity’ (silent breaks during tasks B1–B3), alternative selection (task A2, A4), ‘encoding/recall’ (tasks C1–C4), and calculation (task C5 and sign task during the driving). The overall

Table 6. Classification of visual events

CLASSIFIED AS	CONDITIONS				
	No activity	Register an image	Detect difference	Read a symbol	Scan / search
No activity	7182	1153	23	31	29
Register an image	1783	5019	30	693	43
Detect difference	203	69	1821	827	410
Read a symbol	152	35	56	6420	53
Scan / search	118	22	429	589	1843
TOTAL	9438	6298	2359	8560	2378
Sensitivity (SE)	76.1%	79.7%	77.2%	75.0%	77.5%
PPV	83.3%	66.3%	63.1%	44.8%	85.5%

Table 7. Classification of gross motor events

CLASSIFIED AS	BEHAVIORS			
	No activity	Alternative selection	Encoding/recall	Calculation
No activity	7069	1003	241	193
Selection	1847	4587	493	472
Encoding/recall	382	426	2948	481
Calculation	140	285	511	2458
TOTAL	9438	6301	4193	3604
Sensitivity (SE)	74.9%	72.8%	70.3%	68.2%
PPV	83.1%	62..0%	69.6%	72.4%

classification accuracy (shown again for a classifier developed on combination of subsets of feature vectors from both times of the day) amounted to 72.5 % (Table 7).

4 Discussion

The current study sought to develop a physiologically-based method for workload assessment applicable in the challenging automotive setting. We addressed this need by designing a comprehensive, sensitive, and multifaceted workload assessment tool that incorporates the already established theoretical workload framework that both: (1) covers the different types of workload employed in complex tasks such as driving, and (2) helps define the necessary atomic tasks for building the model. The experimental results suggested that the classifier benefits from combination of complementary input signals (EEG and ECG), better coverage of the scalp regions by an increased number of EEG channels, inclusion of concurrent physiological measurement of fatigue and alertness levels, and short-term signal history. We aimed to overcome the individual variability inherent in the physiological data by including the relative PSD variables in the feature vector. The generalization capability of the trained model was tested by using leave-one-subject-out cross-validation. The proposed method demonstrated that physiological monitoring holds great promise for real time assessment of mental workload.

In the future, we plan to extend the model validation to other simulated environments (flying simulator at Systems Technology Inc.) and real pertinent environments (fully instrumented HMMWV at the Operator Performance Laboratory at the University of Iowa). We also plan to refine the existing atom tasks, especially in the cognitive and visual areas. Alternative classification algorithms such as multi-label learning [21] will be evaluated to facilitate the process of resolving the conflicts between different workload types. The classifier will, finally, be validated on a much larger sample of subjects (target N = 150 subjects).

The ultimate PHYSIOPRINT workload assessment tool is envisioned as a flexible software platform that consists of three main components: (1) an executable that runs on a dedicated local (client) machine to acquire multiple physiological signals from one or more subjects, processes them in real time, and determines global and resource-specific workload on a fine time scale; (2) a large server-based database of physiological signals acquired during relevant atomic tasks from a large number of subjects with different socio-demographic and other characteristics (e.g., degree of driving experience); and (3) a palette of real-time signal processing, feature extraction, and workload classification algorithms. The platform will support a number of recording devices from a wide range of vendors (via the appropriate device drivers), and enable visualization of the workload measures. The users will essentially be able to build their own workload assessment methods from the available building blocks of feature extraction methods and implemented classifiers. Initially, the database will include 100–150 subjects, but we envision that the database will continue to evolve as the community grows in the following years.

Acknowledgments. This work was supported by the Army Research Laboratory grant W91CRB-13-C-0007. The views, opinions, and/or findings contained in this article are those of the authors and should not be interpreted as representing the official views or policies, either expressed or implied, of The Army Research Laboratory or the Department of Defense.

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