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Biosignals in Human Factors Research for Heavy Equipment Operators: A Review of Available Methods and Their Feasibility in Laboratory and Ambulatory Studies

AMIN HEKMATMANESH[1], VICTOR ZHIDCHENKO [1], KARI KAURANEN[2], KAIJA SIITONEN [2], HEIKKI HANDROOS (MEMBER, IEEE) [1], SARI SOUTUKORVA[2], ASKO KILPELÄINEN[2]
[1]Laboratory of Intelligent Machines at LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland
[2]LAB University of Applied Sciences, Yliopistonkatu 36, 53850 Lappeenranta, Finland

ABSTRACT Heavy equipment operation is a responsible and difficult task causing mental workload on a human operator and exposing the operator to a range of harmful factors. Human factors and ergonomics in heavy equipment design have traditionally been focused on anthropometry and questionnaires. More advanced techniques involving biosignal measurements were not applied to heavy equipment, mainly due to the diversity of real working conditions that were hard to reproduce in a laboratory environment and that prevented ambulatory studies. Recent advances in wearable biosensors and real-time simulators produce the capability of using biosignals for improving the ergonomics of heavy equipment operation. The present paper reviews the use of biosignals in human factors and the ergonomics of heavy machines by focusing on stress detection for the last ten years. The aim of the paper is analyzing the previous implemented algorithms to find a set of biosignals and methods of stress identification that could be suitable for identifying stress in heavy equipment operators both in laboratory and ambulatory studies. The conclusion emphasizes successful stress identification methods and a combination of the algorithms from different studies that facilitate the use of heavy equipment operator's applications. Also, feasible methods and directions for future research are considered.

INDEX TERMS Human Stress Detection, Pattern Recognition, Biosignal Processing, Human Factors and Heavy Equipment Operator Ergonomics.

I. INTRODUCTION

Heavy equipment is utilized in construction, mining, and agriculture is a powerful but dangerous tool. It can negatively affect an operator, exposing him to a high level of whole-body vibrations, durable static postures, noise, sunlight, dust, and a wide range of temperature. At the same time, the operator working in harsh conditions must provide high productivity and safe operation since inefficiency and mistakes in operation can be expensive and dangerous.

The above-mentioned items lead to the necessity of paying special attention to human factors and ergonomics at the design phase of heavy equipment and to monitoring of the operator state during his work. Extending traditionally used anthropometry and questionnaires with biosignal measurements is a modern approach in ergonomics that is widely used in aviation [1], intelligent cars [2], manufacturing [3], and marketing [4].

In the field of heavy equipment design, the main focus is on ensuring safety, accounting for anthropometrics, and protection from harmful external factors [5], [6] such as whole-body vibration [7]. The affective states of the operator, such as stress, arousal, and fatigue are taken into account to a lesser extent. Recent advances in wearable biosensors, telecommunication and computing technologies, and machine learning allow filling this gap.

In the present paper, our contribution is in reviewing

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the utilized methods and considering the limitations, pros, and cons for identification of stress vehicle drivers and heavy equipment operators (HEOs), and in considering the possibility of applying suitably analyzed methods for vehicle driver's stress identification for HEOs, both in laboratory and ambulatory studies. The focus of our review is on stress identification since the stress level directly influences the performance and health of the operator. Moreover, the use of biosignals in human factors and ergonomics research is considered for the last ten years of studies. We also consider and emphasize the use of real-time simulators of heavy equipment as a convenient way of making laboratory studies closer to a real working environment. The paper concludes with a set of selected biosignals and data processing methods that can be suitable for stress detection in HEOs and with directions for future research.

The present study, continues in the following steps: Section II: Definition and physiology of stress and influence of stress on the HEO's efficiency; Section III: Real-time simulators and utilized methods for operator's health monitoring and stress detection; Section IV: Concepts of implemented stress identification algorithms; Section V: Discussion; and Section VI: Conclusion.

II. DEFINITION AND PHYSIOLOGY OF STRESS AND INFLUENCE OF STRESS ON THE HEO'S EFFICIENCY

Stress can be defined in at least three different aspects. The first definition states that stress results from pressure (a stimulus-based definition) [8]. The second definition states that stress is a response to noxious stimuli (a response-based definition) [9] and the third definition states that stress is a dynamic process that reflects both internal factors (characteristics of a person) and external factors (harmful stimulus in the vicinity) as the interactions between them (stress as a dynamic process) [10]. Based on the second definition, Selye et. al. [10] conceived the model for physiological response to stress. This template is called the general adaptation syndrome, and it consists of three stages. The first stage is the alarm reaction; during that phase, the body is alerted by the sympathetic nervous system. The second phase is resistance reaction, where the body prepares to deal with the stress, and the capacity of the body to resist stress increases. Both the first and second phases increase the performance of the subjects. However, if the stress reaction continues for a long time and exceeds the capacity of the body to respond, the systems of the body will be injured. This third phase of the process is the stage of exhaustion [9].

A. PHYSIOLOGY OF STRESS

In short, stress affects human physiology in three phases: (1) alarm, (2) resistance, and (3) exhaustion. In the alarm phase of the stress reaction, homeostasis of the body, tissues, and cells change. The metabolism of the body accelerates, and the physiologic responses to stress are mainly caused by the activation of the sympathetic nervous system and the hypothalamic-pituitary-adrenal axis, in which neuromuscular, endocrinologic, and cardiovascular systems activate. In the alarm phase, stress is primarily a consequence of increased plasma concentrations of catecholamine hormones. These hormones accelerate Heart Rate (HR) and Breath Rate (BR) frequency, raise Blood Pressure (BP), increase muscle tonus, and liberate nutrients (glucose and fat) for muscular action. These changes in body momentarily increase the physical and psychical performance of subjects [11].

B. MENTAL STRESS

Mental stress at work, also known as mental workload, is directly related to the proportion of mental capacity an operator expends when performing tasks. The measurement of mental workload is the specification of that proportion [11]. Tao et al. [12] suggested that mental workload is caused by task demands, while task load is more focused on the human body. Mental workload is the "level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support, and past experience." Mental workload could be induced by task demands, stress, and fatigue.

C. PHYSICAL STRESS

Physical Stress is defined as the force applied to a given area of biological tissue, and it may affect musculoskeletal (bone, muscle, tendon, ligament, and cartilage), integumentary (skin), cardiopulmonary/vascular (heart, blood vessels), and neuromuscular (neurons) organ systems of the human body [13]. During routine work, tissues accommodate to physical stresses by altering their structure and composition to meet the mechanical demands [14]. The strain of tissues occurs along a continuum from acute micro- or macrotraumatic injuries or from chronic overuse or overload, poor motor control, posture and alignment, physical activity, and occupational, leisure, and self-care activities and may result in damage to structural protein and the blood supply. The general work-related injuries of upper limb are muscle fatigue and pain, tendon-related disorders (e.g., epicondylitis), carpal tunnel syndrome and cramping of the hand and forearm, and low back injuries caused by disc degeneration or a disc prolapse [15].

In the resistance phase of a stress reaction, the body enhances its capacity to resist stress. The increasing use of energy is an adaptive mechanism of the body to react to changing demands of the environment. Activation of the energy system and high corticosteroid concentrations lead to other physical adaption changes in the body, which include the elevation of core temperature and increased arousal and cardiovascular functions. These changes mainly increase the performance of subjects, but some detrimental aspects (e.g., insomnia, high BP, and weight loss) appear as well. A continuous accelerated metabolic condition may drift into exhaustion [11].

The exhaustion phase leads to the development of pathological process or damage in the body. The immune system of the body works incompletely, and the internal organs are unable to maintain their normal functions. Different symptoms of the autonomic nervous system (e.g., palpitation of the heart, nausea, and perspiration) and infections often exist, and the physical and psychical performances of the subjects crash down [11].

D. HEALTH RISKS OF STRESS

The human body's physiologic responses to a long-duration stress reaction can cause problems in physical and mental health [15]. The prolonged stress reaction has detrimental effects on the function of the cardiovascular system, such as HR, Heart Rate Variation (HRV), BP, and arteries endothelium [16]. These changes increase the risk of myocardial infarction, cardiac arrhythmias, and sudden death [17]. The prolonged stress reaction also affects both the central nervous system (hypothalamus and pituitary), which may cause a decrease in brain mass and the periphery internal organ system (adrenomedullary system) [18]. The chronic stress can lead to depression [19] or Alzheimer's disease [20]. The changed plasma concentrations of hormones induce behavioral modifications (e.g., increased arousal, alertness, vigilance) and physiological consequences (sweating, core temperature, appetite). In addition, the stress has negative effects on many brain functions, such as memory [21], learning [22], and cognition [23]. The stress also negatively affects dynamic and static balance [24], skilled motor performance [25], and driving ability [26], furthers the development of tinnitus [27], and suppresses immune system functions, leading to the development of malignant tumors [28].

1) Environmental Aspects of Stress

The environmental risks at a workplace include physical hazards—noise, temperature, ventilation, vibration, lightning, and radiation [29] [30]. Environmental stress can impair working capacity [31], diminish work safety [32], and increase health risks [33]. Currently, the limitations on these factors to protect the safety and health of employees are defined by international and European standards (to be presented in parts II–E1), and and guidance [11].

Temperature: Temperature. The human body has the ability to regulate body temperature by perspiration, vasoconstriction\vasodilatation, metabolism, and muscular work, but the temperature range and tolerance for optimal body functions are quite narrow and if exceeded can cause the collapse of internal organs. A hot environment leads to heat-related illnesses, such as heat stroke, heat exhaustion, heat cramps, and heat rashes [33]. Protective clothing can create a serious heat stress problem for HEOs [34]. On the other hand, the main cold-related illnesses appear in the respiratory system (asthma), the cardiovascular system (coronary disease), the peripheral circulatory system (Raynaud's disease), the musculoskeletal system (tension neck), and the dermatological system (cold urticaria, freezing injuries), which significantly decrease the productivity of employees [35].

Vibration, Noise and Dust: Vibration, Noise, and Dust. The other external stressors that increase the occupational stress level among heavy equipment operators during the work days are noise, vibration, and dust. At earth-moving workplaces, noise, dust, and body vibration levels are significantly high and cause health disorders. For example, long-term whole body vibration causes lumbar spine injuries [36], and hand-transmitted vibrations cause neurological disorders to the upper extremities and neck-shoulder problems [16]. Dust causes respiratory, cardiovascular disorders, and skin irritation [37].

E. INFLUENCE OF STRESS ON THE PERFORMANCE OF HEOS

In order to analyze the performance influence of different carriers, specifically HEOs, several standards have been defined as follows: Occupational Health and Safety Organizations, NIOSH (National Institute for Safety and Health) [10], EU-OSHA (European Agency for Safety and Health at Work) [38], ILO (International Labour Organization) [11], and national institutes such the Centre for Occupational Safety in Finland [30], and the Finnish Institute of Occupational Health [29] [39]. The organizations at workplaces have the same purpose—to protect the health and safety of the employees and employers and support their well-being at work. Each of the standards concerns a different combination of factors, such as physical risks, handling loads, awkward positions, repetitive work, risk factors (temperature, ventilation, noise, vibration, and radiation) [40].

1) Ergonomic Conditions and Standards For Risk Control Factors Of Physical Stress

The known reported risk factors for work-related musculoskeletal disorders are excessive repetition, awkward postures, and heavy lifting [41]. The extrinsic risk factors are ergonomic environment [15] that studied as static postures or ergonomic topics. Ergonomic posture solutions, such as a well-designed structure of the cabin, seat, steering devices, and pedals, help prevent awkward posture. A vibration prevention solution: seat shock absorbers to dampen frequencies between 1 to 20 Hz and a seat with a vertically moving backrest reduced vibration motion between the seat backrest and the vehicle floor [42]. An upper limb repetition disorder solution: using a joystick that reduces risk factors in upper body limbs compared to steering wheels [43]. Therefore, to control physical risk stress, different standards have been defined, as follows:

- Earth-moving machinery: EN-ISO 3411:2007 is related to the physical dimensions of operators and the minimum space envelope around the operator [18].
- Safety of machinery: EN 547-3 is related to human body measurements.
- Earth-moving machinery: ISO 11112 is related to operator's seat dimensions and requirements, which include

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knowledge of designing the structures and dimensions of the cabin [41].
- Safety of machinery: EN 1005-4 + A1 is related to human physical performance, evaluation of working postures, and movements in relation to the machine [44].
- Static posture: ISO 11226:2000 is related to the evaluation of static working postures based on current ergonomic knowledge [22].
- Whole-body vibration: ISO 2631-1 defines the evaluation of human exposure to whole-body vibration [45].
- The standards ISO/CD 11228-3 (ISO 2003), EN 1005-3 (CEN 2002), and prEN 1005-5(CEN 2003b) offer useful knowledge to designers and manufacturers of machines to avoid structures and devices causing awkward working postures [19]. The standards are designed based on ergonomic postures in biomechanical science and experiments, without using biosignals such as an EEG, EMG, or ECG in HEOs' health monitoring.

III. REAL-TIME SIMULATORS

Real-time simulators have been known as a powerful tool for product development and training for more than a century [46]. They have been widely used to evaluate how an operation environment affects a trainee and how the new design of a machine will affect its driver in the aerospace, locomotive, marine, and car industries. Advances in computer hardware and simulation methods development have greatly simplified the process of real-time simulator creation. A modern system consisting of an operator seat installed on a motion platform and equipped with a set of controls, a visualization display, a sound system, and a powerful computer with simulation software allows the creation of real-time simulators for different types of machines. Such a system can simulate cars, trucks, tractors, excavators, wheel-loaders, cranes, forestry, and mining equipment by running different simulation models without hardware modifications. This has extended the boundaries of real-time simulation from "high-tech" to "practical" applications in the construction, mining, forestry, and agriculture segments. Examples of real-time simulators are depicted in Figure 1.

Data presented in Table 1 and Table 2 show that simulators are widely used in stress identification studies. An advantage of using them in research related to heavy equipment operators is the possibility of keeping different environmental parameters under control. By varying the sound and vibration levels, lighting and visibility conditions, temperature and humidity, and electromagnetic field, it is possible to study the influence of environmental parameters on the operator's condition. Another advantage is the capability of changing design parameters of a machine and studying the influence of these changes on the operator. A wide set of controllable and monitored machine parameters delivered by the simulator, combined with a set of biosignals obtained from the operator, provides ample opportunities for creating efficient cyber-physical systems. For health monitoring (physical and mental), different instruments are used. They are explained in the following sections.

IV. MOVEMENT ANALYSIS FOR DIAGNOSING PHYSICAL STRESS BASED ON OBSERVATION AND VIDEO RECORDING

Physical stress caused by posture and motions at work is measured by different observation approaches. These measurements are based on video recording and quantitative analysis by observations such as OWAS (Ovako Working Posture Assessment System), RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), and OCRA [19]. These ergonomic assessment tools are used to evaluate selected body postures, forceful exertions, type of movements and repetition.

A. OWAS METHOD FOR HEALTH MONITORING

OWAS is the visual evaluation by a video camera for whole-body working and awkward positions. OWAS considers in detail the posture of the back, upper limbs, feet, and the force demanded during the work cycle. In the OWAS method, evaluations of different postures are performed once a minute, and each posture is marked on a worksheet using its code. A posture summation indicates possible overload during the working day. The OWAS method has been applied mainly in manufacturing industries, healthcare and social assistance activities [16].

B. RULA METHOD FOR HEALTH MONITORING

RULA was developed for evaluating the postural load of job tasks on the neck, trunk, and upper extremities and the required force and repetition during the most difficult work tasks. The postures are marked and graded on a single-age worksheet. The final score represents the level of musculoskeletal risk [16].

C. REBA METHOD FOR HEALTH MONITORING

REBA was developed based on RULA. It is applied primarily in healthcare services and service industries. REBA is used for evaluating the trunk, neck, and legs and to the human-load interface coupling the upper limbs. The positions are scored and then processed to provide a combined risk score [16].

D. OCRA METHOD FOR HEALTH MONITORING

OCRA is an evaluation method for the risk assessment of repetitive strain injury in the upper limbs [19]. The evaluation is based on video analysis during repetitive movement tasks while the operator applies shifts that consist of several technical actions (reach, move, grasp, grasp with the other hand, grasp again). The final OCRA index is the combination of defined codes for movements and positions of the humeroscapular joints, elbows, wrists, and finger grips. The calculation model uses multiplier factors for force, posture, complementary factors, and lack of recovery [16].

FIGURE 1. Examples of heavy machine simulators (Laboratory of Intelligent Machines, LUT University, and www.mevea.com)

E. UPPER LIMB HEALTH MONITORING

The Upper Limb expert tool was developed at the Finnish Institute for Occupational Health. It is based on a simple presence/absence scale of hazards, such as repetitive use of the hand, the hand force, and awkward postures. The more "yes" answers there are to the presence hazard, the greater the risk [28].

F. COMPUTER-BASED MOTION INSTRUMENTS FOR PHYSICAL HEALTH MONITORING

Systems for health monitoring, which are based on different sensors, can provide more reliable data than assessments.

One of the useful health monitoring systems is the XSENS system, which obtains data from an accelerometer, gyroscope, and magnetometer to estimate the orientation and position of a body segment. In addition, the XSENS system computes 3D joint kinematics and analyzes motion without external emitters and cameras [20].

The system for assessing the trunk and lower limb joint kinematics is the Xsens MVN Awinda with 17 wireless sensors fitted in a suit. The inertial sensors (MVN Awinda) provide ambulatory motion analysis of the trunk and limb joints, which is performed in real-time. The Industrial Athlete system combines inertial sensors, biomechanical models, and load weights.

The motion capture system enables ergonomic analysis under real working conditions in real-time. The frequent load types such as force, force posture, and repetition can be identified for each body region and evaluated according to the biomechanical and ergonomic criteria [21], which is suitable in a heavy machine workplace environment.

G. BIOMARKERS FOR STRESS DETECTION

Several parameters of biofluids can be used as physiological biomarkers of stress. The fluids suitable for analysis are blood, saliva, and sweat. The cortisol level is known as a good indicator of stress. The lactate level can be used to track body exertion, and the glucose level shows the overall fatigue level. This paper excludes biomarkers from consideration since their use appears to be inconvenient for HEOs, being invasive in case of a blood test or requiring additional actions from the operator in case of a saliva test. An overview of the methods involving biomarkers for stress detection can be found in [47]. The state of the art in the understanding of biomarkers present in sweat under stress and emotional events is considered in [48].

Analysis of sweat provides an interesting opportunity with the recent advancements in on-skin patch-like sensors. This type of sensor is actively studied at the moment in sports medicine [49]. Although the amount of sweat generated in sports activities is much greater than in heavy equipment operation, the ability to continuously monitor the chemical composition of sweat using noninvasive methods looks promising for detecting stress in HEOs. It is an interesting opportunity for future research.

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1) Biosignal Measurement Instruments for Mental Health Monitoring

The methods described above measure the reactions of the autonomic nervous system and the activities of the sympathetic and parasympathetic nervous systems. Health monitoring of the HEOs originated from fatigue, stress, and confusion during multiple complicated tasks. Therefore, studies usually focused on utilizing the biosignals for monitoring the operator's health recorders such as electrocardiography (ECG), BP, BR, Galvanic Skin Response (GSR), photoplethysmography (PPG), body temperature, electroencephalography (EEG), and electromyography (EMG). In the next section, biosignal instruments and successful mathematical methods for detecting stress are considered.

V. CONCEPTS OF IMPLEMENTED STRESS IDENTIFICATION ALGORITHMS

In this section, we first present the steps in stress identification algorithms. Then, the employed sensors for stress identification are introduced. After that, the effective relative stress identification studies for drivers and heavy equipment are evaluated. In order to identify stress patterns, different approaches have been developed that follow the same concept. Conceptually, algorithms are divided into five main steps, which are illustrated in Figure 2 and explained as follows:

I) pre-processing: includes signal segmentation (also called windowing), filtering, and normalizing signals. Filters are designed based on the frequencies that the patterns generate [50];

II) Feature extraction, which defines the functions that reflect a specific behavior in a biosignal. In recent studies, a large number of new features have been extracted [51]–[55]. For example, Lanata et al. [53] designed three driving scenarios for applying stress. In total, 42 features were extracted for detecting three levels of stress. A short list of effective biosignal features from the ECG and GSR in the reviewed studies (tables 1 and 2) are HRV [56], HR [57], difference and phasic-tonic components of EDA signals [58], inter-beat-interval (IBI) [59], wavelet components [55], [60], non-biosignal features extracted from video (head movement and the mean level of the eye opening) [51], environmental data (light, darkness, fog) [50], and GPS position [61].

Also, a short list of useful features from EEG signals includes amplitude, mean, variance, standard deviation (STD), first absolute deviation (FAD), skewness, kurtosis, zero cross, power, and energy, fractal dimensions Sevcik, Higuchi and Katz, chaotic algorithms: largest lyapunov exponent, optimized wavelet packets with detrended fluctuations analysis (DFA), and common spatial patterns [62];

III) The second important part of stress identification is using appropriate feature selection algorithms. The aim of feature selection algorithms is to remove irrelevant features from processing such as linear discriminant analysis (LDA), and principal component analysis (PCA) [63]. Since a set of extracted features can be redundant, a process of selecting the most informative features is important. For example, Lee et al. [54], [64] extracted 46 features from biosignals and vehicle sensors, of which only 22 features were diagnosed as informative features using a stepwise feature selection algorithm. Therefore, the computed features are not effective or necessarily required to be reduced.

Some feature selection algorithms achieve better results with a specific classifier's decision-maker. For example, Dobbins et al. [65] computed a feature pool that included 26 types of features, and then the RELIEFF algorithm was used to select features. Different classifiers were then tested to find the best match to the selected features as an ensemble classifier.

IV) Feature classification: the algorithms for categorizing the selected features among defined classes. Different investigations have been employed to find the best classifiers for the selected features. The evaluation is performed by comparing the obtained accuracies from different classifiers, which are in three categories of predefined [54], [58], [59], [66], combined [65], and new/optimized developed classifiers [67]. For example, Hekmatmanesh et al. [63], [68] employed a set of different predefined classifiers and compared them with optimized predefined classifiers such as generalizing SVM and generalizing RBF methods. In a recent combined classifier study, Rastgoo et al. [50] classified the combined features of the convolutional neural network (CNN) and long short-term memory (LSTM) using the deep learning (DL) classifier. In short, the reliable methods in real-time experiments use a combination of non-linear feature selection algorithms with an ensemble classifier that simultaneously takes advantage of optimization methods [65], [69].

The employed classifiers for HEOs' and vehicle drivers' stress detection are Support Vector Machine (SVM), MultiLayer Perceptron Neural Network with Back Propagation (MLP-NN), K-Nearest Neighbor (KNN), DL, RBF kernel, Neural Networks (NN), KNN, Nearest Mean Classifier (NMC), Bayesian Network, Layer Recurrent Neural Networks (LRNN), Decision Tree, Extreme Learning Machine (ELM), Fuzzy c-means clustering and Logistic Regression, (LR), as shown in tables 1 and 2;

V) The final step is the statistical analysis of the results, which includes accuracy, specificity, sensitivity with paired t-test, ANOVA, Wilcoxon Signed Rank, and post-hoc significance analysis by Tukey correction tests. Accuracy is computed with four main parameters: True Negative, False Negative, True Positive, and False Positive [70]. The combination methods have been used to reach persuasive precision in drivers' stress detection [66], but each step of the identification algorithm has the potential of amending by adding suitable optimization algorithms for the HEO applications. In the next part, relative studies for stress detection for drivers are presented based on the employed sensors.

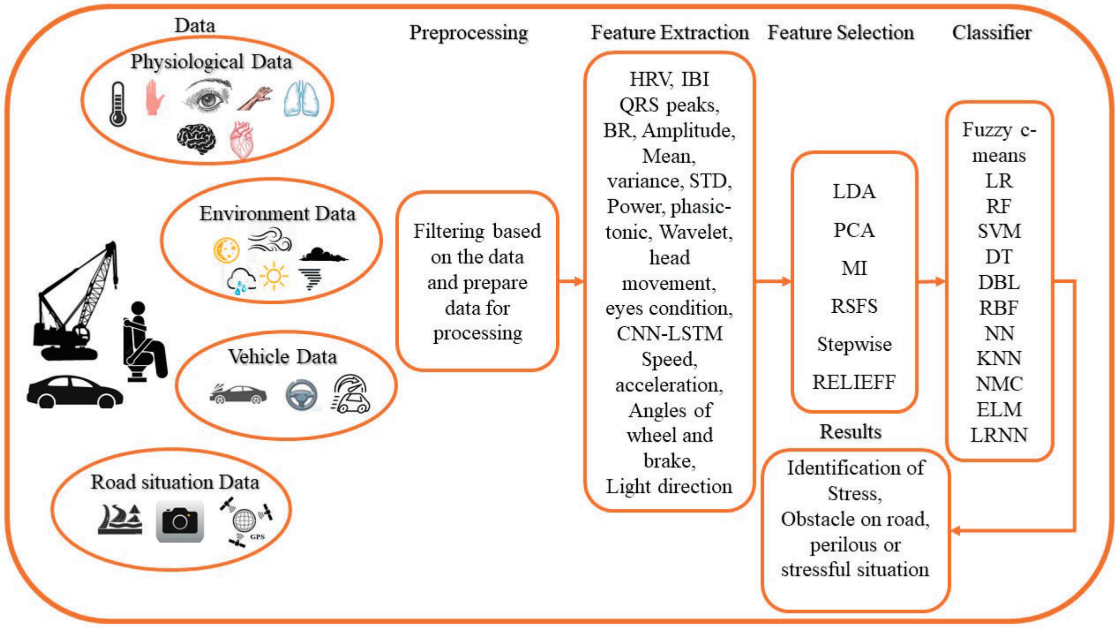

FIGURE 2. The flowchart of the main concept of the stress detection and identification algorithms. The presented methods are some of the implemented algorithms in the studies.

A. THE ROLE OF SENSORS IN VEHICLE DRIVER'S AND HEO'S STRESS IDENTIFICATION APPLICATIONS

In order to create automatic stress identification algorithms, several methods have been developed based on different biosignals, tasks, and applications. Our focus is on the methods and algorithms that can be applied to heavy equipment operators. We also consider the methods designed for vehicle driver's stress that can be suitable for HEOs. The employed biosignals for stress identification are considered individually as follows.

1) ECG Role in Stress Identification

Depending on the level of stress, the functionality of the heart alters. Therefore, an ECG signal that reflects heart activity can be used to identify stress. Some of the useful extracted features from the ECG signal for studying stress are HR, the interbeat interval (IBI), and the variations in the IBI value from beat to beat (known as HRV). Well-established techniques for stress evaluation using the ECG signal are described in [71]. Traditional methods for obtaining a reliable ECG signal and processing the ECG signal in time and frequency domains are provided in the guidelines of the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [72]. In an effort to standardize reporting on the HRV research in psychiatry and related disciplines, these guidelines where later supplemented with a GRAPH checklist [73].

The stress reaction accelerates HR and decreases HRV. The HRV measurements and analyses are divided into the time and frequency domain methods. In the time domain method, the most common calculated parameters are HR, SDNN, and RMSSD. SDNN is the STD of the normal R-R intervals during ECG recording; it is the "gold standard" for the medical stratification of cardiac risk [74]. RMSSD is the root mean square of successive differences between the normal heartbeat; it mainly estimates the parasympathetic regulation of the heart. In the frequency domain methods, the high-frequency component (0.15 to 0.4 Hz) indicates parasympathetic nervous system and vagal activity. The relationship between the low-frequency component (0.04 to 0.15 Hz) and the high-frequency component (LF/HF) denotes sympathetic nervous system activity. That ratio is used to determine the balance of the autonomic nervous system [74]. Based on the above-mentioned findings, HRV is an acceptable method to measure stress in the human body [16].

The application of ECG-based methods for HEOs requires consideration of several peculiarities related to the operation task and work environment. Heavy equipment operation is accompanied by the operator's body motion, vibration, and electromagnetic fields, which can be a source of artifacts in the ECG signal. Since condition-monitoring of operators should be performed automatically, artifact detection methods play an important role in heavy equipment applications. The other important signal for revealing stress is the EEG signal, which is considered in the next part.

2) EEG Role in Stress Identification

The EEG device is effectively helpful in identifying stress and fatigue. Under a high level of stress/fatigue, there is a loss of concentration. That causes significant changes in alpha (8 to 12 Hz) and beta (12 to 38 Hz) waves. For instance, alpha waves disappear or gradually diminish during concentration lapses and drowsiness. On the other hand, if attention increases abnormally, the rate of alpha waves increases abnormally, too [75].

Stimulators such as stress causes frequency changes in neural activity [75] and generates specific patterns in the EEG after onset of the stressor, namely event-related potentials (ERPs). For example, Brookhuis et al. [76] designed a health monitoring system for driver workload using ECG and EEG signals. In the health monitoring algorithm, features such as HRV and HR were extracted from the ECG signal, and ERP features extracted were from the EEG signal. The reason for the insignificant results was the varying ERPs when the subjects change. The authors claimed that stress at different ages produce different P300 patterns (positive peaks after 300 ms onset of stress) in brain neurons in different situations. The EEG signals contains valuable information that is a reflection of stressors.

Afterwards, Noh et al. [77] used the EEG and ECG biosignals to identify stress on three levels and consider productivity in the experimental HEO's tasks. In the algorithm, entropy of frequency-based features from the EEG, HRV, and environmental data were extracted for stress identification. It is concluded that stress changes the productivity of the subjects as operators. The disadvantage of employing the EEG signal for stress detection in the HEO experiments is that the EEG is sensitive to noise and it can be easily contaminated in HEO applications (high level of sound and vibration). Therefore, the EEG is not the most suitable biosignal for detecting stress in real working conditions, but for heavy machine simulators, it can be useful because noises are controllable in the simulators. The solution for HEO applications is designing cabins with the special properties of diminishing noises. The advantage of using a clear EEG signal is that it can compute relevant information about the operator's condition and has can detect stress in the early stages. The next biosignal for stress identification is the EMG, as explained below.

3) EMG Role in Stress Identification

Investigators study the relationship between muscle activity and psychophysiological stress response because there is high prevalence of musculoskeletal disorders associated with stressful work [78]. In stress research based on the EMG, the trapezius, sternocleidomastoid, and masseter muscles are commonly studied. The results of these studies have addressed significantly higher amplitudes of EMG signals during stressful situations compared to rest periods [56], [79]. On the other hand, some studies confirmed that EMG is not good for stress identification. Wen et al. [61] applied short-term stress on the drivers in a real car race experiment to find out how the human body reacts to real stress. In the experiment, a combination of EMG (masseter muscle), HRV, and GSR signals was employed. In the stress detection algorithm, a camera and GPS were also used for monitoring the driver and the car position. The results showed that GSR and HRV were strongly related to stress, and EMG did not contain enough stress information. Stress patterns in the EMG signals were not revealed well, and they were highly dependent on the subject. The disadvantage of EMG signals for HEOs is that vibration may affect the signals significantly. In general, the EMG signal, as well as respiration, BP, and GSR signals, are counted as complementary signals that provide supplementary information for stress identification. The GSR role in stress detection is considered in the next part.

4) GSR Role in Stress Identification

GSR is the electrical phenomenon in human skin collectively known as Electrodermal Activity (EDA). GSR measurements are performed with a wearable sensor based on the phenomenon that skin conductance varies following the state of sweat glands in the skin. Since sweating is controlled by the sympathetic nervous system, the GSR indirectly measures the activity of the sympathetic nervous system and a human reaction to physical and psychological stress. When psychological or physiological arousal increases, sweat gland activity also accelerates, which leads to a decrease in skin conductance. Measurement and analysis of the GSR uses the above-mentioned physiological features to estimate the stress level in humans [80]. Recommendations for performing electrodermal measurements can be found in [81]. Although the EDA is frequently used as a stress indicator during the presentation of different stressful stimuli [82], and presents demonstrated sensitivity to workload and emotional strain [71], it is prone to artifacts in nonlaboratory settings. This creates obstacles for EDA measurements in the working environment of the HEOs. The important issues of ambulatory skin conductance recording in HEO applications are the stability of the electrodes and the influence of temperature and physical activities [81]. The next biosignal for considering stress for HEOs applications is the respiration signal, which is considered next.

5) Respiration Role in Stress Identification

A higher rate of breathing is a symptom during stress in comparison with normal situations. The respiration signal is usually recorded at a low-frequency sampling rate such as 3 Hz, which does not have enough information for detecting stress individually. Therefore, the BR signal is usually used with other signals such as ECG, GSR, and EMG to detect stress [51], [55], [60]. For example, Soman et al. [83] used the driver's ECG and respiration signals for identifying stress. The designed algorithms were based on the correlation between the QRS and BR features and stress situations (Table 1). The QRS is a combination of a Q wave, R wave, and S wave in the ECG signals, representing ventricular depolarization. In another investigation, Singh et al. [84] completed the previous study [85]using hybrid biosignals consisting of ECG, EMG, GSR, and BR to detect stress on three levels (low, moderate, and high stress). The results are presented in Table 1. The algorithm developed in the study [84] was not applied to a real-time system, so its

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usability in such applications is unclear. In conclusion, the respiration information can be used as complementary data for stress identification in HEO applications.

6) Hybrid Methods and External Sensors in Stress Identification

Hybrid methods combine different biosensors for data acquisition and produce more reliable results for health monitoring. Each biosignal has specific hallmark features for stress detection, and the hybrid methods combine them in one algorithm. Several studies successfully employed hybrid methods [61], [76], [84]. For example, Brookhuis et al. [76] investigated drivers' mental workload in driving simulators using the ECG and EEG signals. In order to detect stress and fatigue, an algorithm based on the selective features was designed, namely the HRV and HR features from the ECG signals and ERP (P300) features from the EEG signals. The obtained results depicted that stress generated P300 patterns in the EEG, which varied for different situations and age groups.

Researchers are interested in employing signals with less complexity compared to the EEG, such as ECG, EMG, BR, Photoplethysmography (PPG), and GSR [56], [83], [85]. Biosignals such as PPG, GSR, BR, and BP contain complementary information, which means that they are not enough to be employed individually in the identification algorithms [85]. Among the less complex signals, the ECG signal is known as the most informative for stress detection and health monitoring [57], [86]. A short list of obtained effective ECG features for health monitoring in heavy equipment applications includes HRV, HR, QRS peaks, BR, amplitude, and power in different task situations.

Environmental parameters play an important role in operator's stress in driving a vehicle or a heavy machine. Recent studies on detecting stress, fatigue, and concentration lapses are based on a combination of biosignals and extra sensors, such as the camera [65], vehicle parameters (steering wheel, gas and brake angles, and speed) [50], weather sensors (rain, fog, light and sun direction) [50], GPS position [61], and traffic information by eCell [58]. Some of the above-mentioned extra sensors have been employed in semi-autonomous vehicle design for predicting hazardous or stressful situations and for generating an automatic break in real experiments [53], [54], [65], [77].

In the latest studies, Rahman et al. [59] designed an algorithm to improve the stress identification accuracy of drivers using vehicle parameters (gas, break, steering wheel and road information) and video processing. In the study, a combination of the external sensor's data (road and weather conditions) with the HRV, IBI and facial images were used for developing an Artificial Intelligence (AI)-based algorithm to assist drivers in stressful (dangerous) situations.

The presented environmental parameters and additional sources of information play a critical role in stress detection. Therefore, accounting for the above-mentioned parameters can improve the results of HEOs' health monitoring and stress detection. The next section is explainsing the development of methods for identifying stress for vehicle drivers and HEOs over time.

B. DEVELOPMENT OF STRESS IDENTIFICATION ALGORITHMS FOR VEHICLE DRIVERS AND HEOS

Working with heavy machines causes health problems over time. This paper reviews the methods that can be applied to HEO health monitoring. Vehicle driving resembles heavy machine operation, which is why we also consider studies related to vehicle drivers. The challenging point in heavy machines is measuring the biosignals in the presence of high-level vibration, sound, and electromagnetic noises. In the discussion part, the development of AI algorithms is also considered in detail.

Identification of stress by the use of only one biosignal does not achieve promising results. Therefore, most of the studies employed hybrid methods [61], [76], [84], [86]. For example, Ahmed et al. [86], employed only an ECG signal to identify stress. The strength of the study was employing a combination of feature selection algorithms named PCA, mutual information (MI), and random subset feature selection (RSFS). Predefined classifiers are then classified as the selected features, namely SVM, random forest (RF), and NN. SVM was reported to be the best classifier (Table 2). The weakness points of the study were the following: (1) Although several parts of the human body are affected during stress, one type of sensor is used for identifying stress; (2) computing a low number of features is one reason for low precision; (3) traditional classifiers were used to identify stress, although it was applicable to optimizing the traditional classifiers; (4) the algorithm response time (delay) was not presented; (5) the variation in accuracies was not presented; (6) employing a low number of subjects, which is important in training a classifier. The limitation of the study was employing a binary classifier to consider the presence of stress instead of using a multi-classifier to classify different levels of stress.

In another similar study, Soman et al. [83] used the ECG and respiration signals to detect stress. The features used were the power of PQRS and BR, which were not reported by the results as a significant achievement. The Soman et al. study has the same weaknesses and limitations as Ahmed et al. [86]. Therefore, samon et al. [56] developed their previous study by using ECG and EMG signals and employing five features to detect stress. The precision of the identified result was a hallmark. In fact, the study reached a high precision of 100%, even though they did not solve the weaknesses of previous studies, which were the low number of features and subjects, the denial of employing feature selection, and using the traditional binary SVM classifier. Soman et al. did not explain the SVM details about the portion of data used for validation, training, and testing.

The next study added the EEG to the previous studies to identify stress. Brookhuis et al. [76] investigated drivers' mental workload in driving simulators using the ECG and EEG signals for drivers. In order to detect stress and fatigue, an algorithm was designed based on selective features, namely HRV and HR from the ECG and ERP (P300) patterns from the EEG signals. The obtained results depicted that stress generated the P300 patterns in the EEG, which varied in different situations and for different age groups. The claimed pattern variation did not let the algorithm achieve a precise result.

Afterwards, several studies were performed to cover the above-mentioned weaknesses. Therefore, a large number of new features were computed [51]–[55]. Rigas et al. [51], [52] developed algorithms that covered some parts of above-mentioned weaknesses by using different types of wearable sensors (ECG, EDA, and RSP) and non-wearable sensors (external sensors, GPS, and camera) for identifying stress. Therefore, a large number of features were extracted for detecting three levels of stress. The algorithm was based on different predefined classifiers that the Bayesian Network known selected as the best classifier. Rigas et al. covered well the weaknesses of the previous study [76] and achieved significant results.

Later, Singh et al. [84], [85] used other combinations of biosignals such as PPG, GSR, and respiration for stress detection, and different features were extracted from the GSR. The strength of the study was in extracting new features not included in previous studies and in achieving results that were not higher than in the previously considered studies. The weakness of the study was in not extracting efficient features and not employing a feature selection algorithm, and the low number of subjects participating in the experiment.

Thereafter, studies focused on producing effective features. Wang et al. [57] implemented an algorithm based on the ECG to identify stress. The strength of the study was in extracting 24 features from the ECG. The rest of the algorithm was using kernel-based class (LDA, and PCA) feature selection algorithms and the predefined KNN classifier. The advantage of the LDA as a feature selection is reducing the number of features by maximizing between-group scattering over within-group scattering. The maximization of between-group scattering enables the algorithm to seek projections that reduce the inter-class variance while increasing the distance between classes [87]. The limitation of the algorithm is the LDA as suitable for binary-based classifiers. By experience, feature selection is based on choosing classifiers, of which LDA/PCA feature selections with K-NN cause significant results compared to the Rigas et al. study [52].

In order to develop the Wang et al. study, Lanata et al. [53] designed an algorithm to detect stress. In the experiment, participants accomplished three driving scenarios for applying stress on three levels. In the algorithm, a total of 42 features were extracted from the ECG, EDA, respiration, and external signals (vehicle parameters) that achieved significant results. The weakness of the method was the absence of the feature selection algorithm and the greater number of subjects. The strengths of the Lanata et al. study were in extracting a large number of features and using vehicle parameters such as speed, which is a factor of stress in driving.

The papers explained above showed that the results were based on different features and traditional classifiers. Some of the next publications [58], [61] used repetitive features and classifiers in different combinations and compared their results with the previously explained studies. The most of employed features are time-based algorithms such as average, power, and difference of GSR values.

In a series of studies, time and frequency features were considered in a different study. Lee et al. [54] used a combination of frequency- and time-based algorithms. Lee et al. considered the Lanata et al. study [53] weaknesses and extracted 46 features from biosignals and vehicle sensors, and then 22 informative features were selected by a stepwise feature selection algorithm. The SVM classifier was then used for predicting the stress level. The stepwise algorithm is a step-by-step iterative algorithm that constructs a regression model based on independent variables. In the model, the strength is that the variables are can be updated in each iteration, and the precision of each iteration is evaluated, since it reaches a fixed model. From another point of view, the advantage of the method is the feature-by-feature evaluation in each iteration that generates the coefficients for constructing the optimum model. The study focused on extracting a large number of features and selecting the best features by a different feature selection compared to other studies. The results showed that the importance of extracting appropriate features and feature selection algorithm. The results might be increased if a larger number of subjects were employed. The weakness of the frequency domain features is lost time in the time series computations. In short, some informative values are lost.

As an effective idea, Chen et al. [55] used the advantages of the previous effective methods, and they cover the frequency domain features by using time-frequency features ("wavelets") that preserve the location of a frequency at a specific time. Chen et al. computed wavelet components and extracted 15 features from the ECG, GSR, and RSP signals. The previous studies [52], [53], [56], [57] achieved higher results in comparison with the Chen et al. study [55], Table 2. The main advantage of wavelets is the employment of a specific wave (the "mother wavelet") that enables the algorithm to search for a specific pattern on different scales and time-shifts. The weakness of the wavelet is its unsuitability for real-time applications due to time-consuming computations, depending on the application, of how much delay is acceptable. El et al. [60] planed to develop Cheng et. al.'s [55] study concept by computing a feature pool of 26 features from a wavelet. The feature space dimension is the reduced using recursive feature elimination algorithm, which the results did not report as significant improvements.

Based on the achievements, it is confirmed that the external sensors (vehicle parameters and environmental conditions) play an important role in stress detection. The external sensors are categorized into three groups: (1) vehicle parameters are the values extracted from a vehicle in each experimental task, such as speed, acceleration (which may alter the driver's concentration), excitation, and stress; (2) environmental features which are the road conditions (possibly dangerous) that may cause stress; (3) weather information, such as a rainy, snowy, slippery, and foggy road; and day and night affecting the visibility of the driver; (4) GPS, which is useful for considering the vehicle position on the road; and (5) video camera, which is useful for extracting facial features, such as drowsiness or awareness of a driver.

Recently, Dobbins et al. [65] computed a feature pool of 26 types of features from the ECG, PPG, external sensors, and camera. Then, the RELIEFF algorithm were used to select features. In the implemented approach, four classifiers were used, namely LDA, KNN, decision trees (DT), and ensemble classifiers, of which the ensemble algorithm achieved the most accurate result. The strengths of the study were in using different external sensors, computing a large number of features, using the effective RELIEFF feature selection method, and employing different classifiers that include the ensemble classifier. Using the ensemble classifier was an advantage because it reduces bias, variance, and overfitting, which leads to a better match with the RELIEFF feature selection algorithm. Dobbins et al. covered most of the weaknesses of the previous studies. The limitation of the study was in using a binary classifier, a low number of subjects, not presenting the time response, and the variation in accuracy for the average values.

Afterwards, Noh et al. [77] used a combination of sensors to record biosignals, vehicle parameters, and environmental condition data. In the algorithm, the focus is on using the EEG and using unsupervised fuzzy c-means clustering for three levels of stress. The advantages of the study is computing new features from the EEG and employing the fuzzy-based clustering algorithm for categorizing features. One challenging point in unsupervised algorithms such as RELIEFF is lower precision due to no label being used during training the classifier. The weakness of the method is the higher error rate due to the use of a clustering algorithm with an inadequate number of features.

In recent studies, Rastgoo et al. [50] focused on two parts of the identification algorithm: (1) extracting features from the vehicle parameters and environment, such as steering wheel, gas and brake angles, speed, light, darkness, and fog, and (2) employing the DL classifier. The DL is based on a combination of convolutional neural network (CNN) and long short-term memory (LSTM) algorithms, followed by the identification of the stress level using the DL classifier. The strengths the study are in extracting different features that help the AI to detect the reaction of the driver in different conditions and using the DL algorithm, which is a powerful classifier. From another point of view, the DL can be the weakness of the method when an inadequate number of features are used. The DL needs a large feature pool to be well-trained in identifying algorithms.

The next recent study is Rahman et al. [59] in which non-biosignal features were extracted from video and vehicle parameters. The extracted features from the video were head movement and facial features such as the mean level of eye opening. The binary LR classifier were employed to diagnose the presence of stress. The study achieved significant results with some weaknesses, as follows: the low number of subjects, feature selection was not used, no reported reaction time, and biosignals were not used. In another recent study, Halim et al. [69] used only the EEG and extracted a combination of frequency-based and time-based (STD) features. The features were categorized by SVM and reached a significant result. The weakness of the study is similar to [59] and [86]. Although development of stress identification for drivers has improved in the last 10 years, recent studies [59], [69] did not take advantage of the previous improvements.

VI. DISCUSSION

Heavy equipment operation has several features that distinguish it from other types of work, such as vehicle driving and manufacturing plant operation. These features should be taken into account when the decision is made to use a particular biosignal or data processing method. This part gives an overview of aspects of heavy equipment operation and discusses the effect they can have on HEO stress-estimation. Heavy equipment operates in diverse environments, ranging from urban area to fields, forests, mines, and quarries. Such conditions as external temperature variations, sunlight, dust, and noise are usual when operating heavy equipment. As a consequence, environmental factors not only influence the stress level of the operator, they also change the operator's physiological parameters, which can affect the applicability of methods developed for other types of work, for example, driving a car. The current trend toward hybridization of heavy equipment increases the number of powerful electric components in a machine.

Electromagnetic noise generated by these components affects low power biosignals such as EEG. This introduces an additional obstacle to the application of existing methods of stress estimation to the HEOs and requires future research. The physiological impact of heavy equipment on the operator includes whole-body vibration combined with static and sometimes awkward postures. These factors produce both physiological and mental stress. At the same time, they are usually eliminated in the case of car drivers.

The number of movements needed to be performed by an operator to control a heavy machine is higher than in car driving. In addition to controlling the movement of the machine itself, the operator must control the machine parts, such as booms and the bucket. It makes the operation more complicated and produces a higher mental load than with car driving. The situation gets worse with the increase in machine complexity, which introduces additional visual indicators and controls in the cabin.

Another important factor is that heavy equipment operation assumes the presence of stress induced by the task being performed. An operator who is focused on the task is often responsible to perform on a tight schedule in collaboration with other workers and machines, which causes some stress. This distinguishes an HEO from the typical car driver, making the driver more similar to a race car driver. The difference is that a race car driver usually performs the driver's task during the relatively short period of the race, while an HEO works under similar conditions for a long shift. The presence of stress as an integral part of work requires a special approach to stress estimation. All of these factors present stress estimation of HEOs as an actual topic for human factors research in the near future.

The development of wearable sensors capable of wireless transmission of biosignals fosters the move of the measurement process from the laboratory environment to the real field. This transition is facilitated by the use of real-time simulators, which provide a convenient way to eliminate unwanted external factors while preserving important parameters that must be considered in real conditions.

Two directions can be identified in the development of methods for stress detection in HEOs. The first one is accounting for stress at the machine-design phase. Using a real-time simulator that reproduces behavior of the future machine, different design parameters can be evaluated for usability. Estimating the stress level of the operator as a function of design parameters, optimal parameters can be found before creating the first prototype of the new machine. The application scenario presented here does not require high performance of the methods being developed. In contrast, stress estimation in real machine operation (which is another interesting direction for future research) involves the development of methods that can operate in real time. Such methods will provide accident prevention and help to increase productivity by adjusting machine parameters according to the state of the operator.

VII. CONCLUSION

The consequences of heavy equipment operation under physical and mental stress, combined with a heavy workload that causes fatigue and loss of concentration, can be dangerous by causing collisions and injury. The development of efficient AI algorithms for stress detection is necessary to avoid injuries and make heavy equipment operators more productive. Some of the health monitoring algorithms applied to vehicle drivers could potentially be used for HEOs. The most informative biosignal features are extracted from ECG (HRV and HR) and GSR data, and the best external features are extracted from vehicle parameters and a camera. An advantage of the ECG and GSR signals in comparison with the EEG signal is that they are less sensitive to noise. Handling noise is a challenge for the EEG in HEO applications. Combining biosignals and external signals is advantageous for predicting stress in heavy machine operation, but the vibration the electromagnetic and sound noise decrease the accuracy of the results.

The data provided in Table 1 and Table 2 show that classification algorithm performance depends on the feature set and on the experimental task for which the stress is analyzed. The most informative features were obtained using different combinations of ECG, GSR, EEG, and EMG signals and external data about the vehicle parameters and environment. The most effective recognized feature selection was LDA and then stepwise algorithms. In binary conditions, SVM and then the ensemble classifier demonstrated superior performance in several studies. Real-time simulators allow keeping environmental parameters under control and provide a convenient tool for stress detection algorithm development for HEOs. Transferring biosignal measurements from the laboratory to a real working environment—developing sensors, algorithms, and heavy machine parts such as a cabin that can operate in real time and in the presence of noise—opens up opportunities for future research.

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TABLE 1. First part of reviewed studies on HEO's and driver's stress identification.

Authors Year	Signal	Features	Classifiers	Best Average Accuracy	Classes	Experimental environment
Ahmed et al. [86] 2010	ECG	R peaks, RR interval, HR	SVM	81.90%	no stress and stress	simulator offline
Brookhuis et al. [76] 2010	ECG, EEG	ECG: HRV, HR EEG: ERP	-	-	low stress high stress	vehicle simulator
Rigas et al. [51] 2011	ECG, EDA, RSP, camera and Environment parameters	ECG: RR variability, DFA, Entropy, EDA: FAD, Respiration: max energy Environment: road visibility, traffic, weather. video processing: eye opening, head movement	SVM, DT, naïve byes Bayesian	SVM: 86.00%	stress fatigue	simulator offline
Rigas et al. [52] 2011	ECG, EDA, RSP, camera, Vehicle data, GPS	ECG: HRV EDA: GSRs differential Respiration: entropy of spectrum camera: road monitoring environment: GPS vehicle data: speed, RPM, and throttle	Bayesian Network	96.00%	no-stress, low stress, medium stress, high stress	simulator offline
Singh et al. [85] 2013	PPG, GSR, Respiration	PPG: HRV, GSR: rise time, peak, energy, percentage decay, Half-recovery time, average rise	LRNN	89.23%	low stress, medium stress, high stress	offline
Singh et al. [84] 2013	ECG, EMG, GSR, Respiration	ECG: HRV, mean HR, rms, EMG: mean, GSR: Mean of foot- and hand, BR	Threshold and NN	NN: 83.43%	low stress, moderate stress, high stress	offline
Wang et al. [57] 2013	ECG	8 features from ECG, 16 features from HRV	KNN	97.78%	low stress high stress	real-time driving
Soman et al. [83] 2013	ECG and respiration rate	ECG: power of QRS and BR	-	-	low stress high stress	simulator offline
lanata et al. [53] 2014	ECG, EDA, RSP, Vehicle dynamics data	42 features: ECG: HRV, BR, ERD: phasic/tonic components Vehicle speed	NMC	91.00%	no stress, stress level 1, stress level 2	real-time
Soman et al. [56] 2014	ECG and EMG	ECG: power of R peaks in QRS and HR EMG: zero crossing, amplitude modulation of envelope	SVM	100%	low stress high stress	real-time

note: Some studies reported the results for individual subjects that we compute the average tables 1 and 2

TABLE 2. second part of reviewed studies on HEO's and driver's stress Identification.

Authors Year	Signal	Features	Classifiers	Best Average Accuracy	Classes	Experimental environment
Lee et al. [54] 2016	GSR and inertial motion sensor	46 features from time-, frequency- and phase domains	SVM	94.78%	no stress stress	offline
Lee et al. [64] 2016	GSR, PPG and inertial motion sensor	20 features from time- and frequency domains	SVM with RBF kernel	95.38%	no stress stress	real-time
Wen et al. [61] 2017	EMG (masseter muscle), HRV and GSR	ECG: R-R intervals, SDNN, RMSDD ratio of SDNN/RMSSD, HRV GSR: GSR signal vehicle parameter: acceleration	-	-	no stress stress	real-time, real race car
Urbano et al. [58] 2017	ECG and GSR	ECG: HRV, HR GSR: amplitude, ECG&GSR: maximum, minimum and average	LDA, SVM	96.00%	no stress stress	offline
Chen et al. [55] 2017	ECG, hand- and foot GSR and RSP	15 wavelet features, spectral- and time analysis	ELM and SVM	89.00%	low stress, medium stress, high stress	offline
El et al. [60] 2018	hand- and foot EDA, EMG, respiration and ECG signals	RF based recursive feature elimination and wavelet components	SVM	-	no stress stress	offline
Dobbins et al. [65] 2018	ECG, PPG, extrenal sensors: smartphone camera, accelerometer	11 features from time- and frequency- domain 16 features from external sensors	LDA, KNN, DT and ensemble	ensemble: 86.90%	no stress stress	real-time
Noh et al. [77] 2019	EEG, ECG, velocity and altitude as environmental data	ECG: HRV EEG: entropy, $Betha/Alpha$ external sensors: altitude, velocity	Fuzzy C-means clustering	-	low stress, medium stress high stress	real-time mode in real traffic
Rastgoo et al. [50] 2019	ECG, external sensors for environment and vehicle	A: LSTM-CNN, HRV mean, STD, square root and new features, B: mean of gas pedal, steering wheel, brake pedal C: Distance to next vehicle Lane width, Number of lanes, day time, weather info	DL	accuracy: 92.8%, sensitivity: 94.13%, specificity: 97.37% precision: 95.00%	low stress medium stress high stress	vehicle simulator in real-time mode
Rahman et al. [59] 2020	Video camera, vehicle parameters	18 features from camera, 8 features from vehicle parameters	LR, LDA, SVM, NN	LR: 94.00%	no stress stress	vehicle simulator in real-time mode
Halim et al. [69] 2020	EEG	frequency-based features, average STD	RF, SVM, NN	SVM: 97.95%	rest stress	vehicle simulator in real-time mode

note: Some studies reported the results for individual subjects that we compute the average of accuracies over subjects in tables 1 and 2

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We present the nomenclature in the manuscript in the appendix.

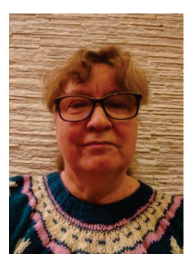
Nomenclature

AI	Artificial Intelligence
BCI	Brain-Computer Interface
BP	Blood Pressure
BR	Breath Rate
CNN	Convolutional Neural Network
DFA	Detrended Fluctuations Analysis
DL	Deep Learning
DT	Decision Trees
ECG	Electrocardiography
EDA	Electrodermal Activity
EEG	Electroencephalogram
EMG	Electromyography
ERP	Event-Related Potential
FAD	First Absolute Deviation
GSR	Galvanic Skin Response
HEO	Heavy Equipment Operator
HF	High Frequency
HR	heart rate
HRV	Heart Hate Hariability
IBI	Inter-Beat Interval
KNN	K-nearest neighbor
LDA	Linear Discriminant Analysis
LF	Low Frequency
LR	Logistic regression
LRNN	Layer Recurrent Neural Networks
LSTM	Long Short-Term Memory
MLP-NN	Multi-Layer Perceptron Neural Network Back Propagation
NMC	Nearest Mean Classifier
NN	Neural Network
OWAS	Ovako Working Posture Assessment System
PCA	Principal Component Analysis
PPG	Photoplethysmography
QRS	Q wave, R wave and S wave
REBA	Rapid Entire Body Assessment
RULA	Rapid Upper Limb Assessment
SVM	Support Vector Machine

AMIN HEKMATMANESH received his bachelor's in Electrical Engineering from Science and Research at Fars University, Shiraz, Iran, 2010. His Master's degree was in Biomedical Engineering from Shahed University in Tehran, Iran, 2013. His Master's thesis was about analyzing Sleep EEG signal processing, learning and negative emotional memory. He received his PhD on brain-controlled ankle foot and hand orthosis and mobile vehicle robots using the EEG in the Laboratory of Intelligent Machines at Lappeenranta University of Technology, 2016–2019. Since 2020, he is working as a Post-Doc on heavy machine operator's health monitoring and signal processing for simulators in the Laboratory of Intelligent Machines at Lappeenranta University of Technology.

VICTOR ZHIDCHENKO received his D.Sc (Tech.) degree at LUT University (Lappeenranta, Finland) in 2019. He holds a Candidate of Sciences degree from Samara National Research University (Russia). He is currently working as a post-doc researcher at LUT University. He is also an associate professor in the Department of Software Systems at Samara National Research University (Russia). His research interests are related to computer simulation, cyber-physical systems, digital twins for heavy equipment, Big Data, cloud computing. and the Internet of Things.

KARI KAURANEN received the master's degree in health sciences from the Faculty of Sport and Health Sciences, University of Jyväskylä, Finland .in 1995, and a PhD degree in human motor performance from the Faculty of Medicine, University of Oulu, Finland, in 1999. He is currently a Principal Lecturer with the Faculty of Health and Social Care, LAB University of Applied Sciences, Lappeenranta, Finland. He is also the Adjunct Professor in Physical Therapy, University of Jyväskylä, Finland. He has about 30 academic papers in accredited journals and peer-reviewed conferences. In addition, he has written 4 textbooks about biomechanics, human motor performance, muscle and physical therapy. His research interests include musculoskeletal biomechanics, neuromuscular control and coordination of human movement.



KAIJA SIITONEN is an occupational physical therapist and received the master's degree, major in ergonomics, from the Faculty of Health Sciences, Kuopio University, Finland, in 2008. She has been working as Occupational Physiotherapist, mainly in a paper, board, and pulp factory from 1986 to 2008, dealing with work-related musculoskeletal disorders and ergonomic problems at workplaces. After that she has been working as a senior lecturer in the Department of Health and Social Care, Saimaa University of Applied Sciences in 2009–2019 and LAB University of Applied Sciences in 2020, teaching occupational physiotherapy and the physiotherapy of musculoskeletal disorders.

HEIKKI HANDROOS received his M.Sc. (Eng.) and D.Sc. (Tech.) degrees from Tampere University of Technology in 1985 and 1991. He has been a professor of Machine Automation at Lappeenranta University of Technology since 1992. He has been a visiting professor at the University of Minnesota, Peter the Great St Petersburg Polytechnic University, and the National Defense Academy (Japan). His research interests range from modeling, design, and control of mechatronic transmissions to robotics and virtual engineering. He has published about 250 international scientific papers and supervised around 20 D.Sc. (Tech.) theses. He has been an Associate Editor of the ASME Journal of Dynamic Systems, Measurement and Control since 2014. He has led several important domestic and international research Projects.

SARI SOUTUKORVA received the degree program in physiotherapy from Saimia University of Applied Sciences in 2011 and received the program of professional teacher education from Jyväskylä University of Applied Sciences in 2020. She will receive a master's degree in health education (minor subjects psychology and HRM) from the University of Jyväskylä in the spring 2021. She is currently working as a teacher at LAB University of Applied Sciences. Before teaching at LAB, she has worked as an occupational physiotherapist.

ASKO KILPELÄINEN received a bachelor's degree in physiotherapy in 2000 from the Jyväskylä University of Applied Sciences and a master's degree in 2004 from the Department of Biology of Physical Activity at the University of Jyväskylä. His master thesis was about Achilles tendon loading while walking in level and sloped conditions. Since 2004, he has worked as a lecturer at LAB University of Applied Sciences in Lappeenranta, and his main teaching topics have been anatomy and physiology and human performance and its measurements. He has also worked as project manager or worker on several projects that focus on Living Lab –development in different areas of welfare. He has also worked for one year as an Academy manager at MBT Footwear Finland in 2009. Since 2019, he has been working as a researcher on heavy machine operator health monitoring and signal processing for simulators together with t Lappeenranta University of Technology.