# Using EEG for Mental Fatigue Assessment: A Comprehensive Look Into the Current State of the Art

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***Abstract*—This paper provides a brief survey of recent developments on the use of electroencephalogram (EEG) sensors for detecting mental fatigue (MF) in human operators during tasks involving human–machine interaction. This research topic has received much attention since there is a consensus among experts on the increasing relation between human failure and accidents in safety-critical tasks. MF is one of the most influential aspects leading to human failure and the most reliable way to assess it is using operator's physiological data, especially EEG. In the past few decades, hundreds of publications have explored the use of EEG alone or together with other objective and subjective measures for assessing MF, drowsiness, and tiredness in human operators. With recent improvements in data preprocessing, feature extraction, and classification algorithms, the monitoring and mitigation of MF in real time has become a reality. This trend is mainly due to the increasing use of machine learning techniques. This paper provides a comprehensive look at the current state of the art in the field of MF detection using EEG, identifying the currently used technique, algorithms, and methods and possible trends and promising areas for further research. The paper is concluded by suggesting a kernel partial least squares discrete-output linear regression based model as an all-around good option for an MF assessment system.**

***Index Terms*—Electroencephalogram (EEG), human factors, human–machine systems, mental fatigue (MF) assessment, risk assessment, sensor fusion.**

## I. Introduction

In recent decades, the greater role human operators play in life-threatening accidents than systems and equipment malfunction or failure has become increasingly clear [1], [2]. Research has demonstrated this in relation to driving [3], public transportation [4], [5], commercial air transportation [6], air traffic control [7], nuclear power plants [8], maritime operations [9], etc. This has prompted explorations into assessments of operator functional state (OFS) as a key means of lowering risk.

Manuscript received October 22, 2018; revised February 19, 2019; accepted July 30, 2019. Date of publication September 9, 2019; date of current version November 21, 2019. This work was supported in part by the project "SFI Offshore Mechatronics" funded by Norway Research Council, Norway (Project 237896) and in part by the project "SFI Marine Operations" funded by Norway Research Council, Norway (Project 237929). This article was recommended by Associate Editor L. Contreras-Vidal. *(Corresponding author: Thiago Gabriel Monteiro.)*

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Digital Object Identifier 10.1109/THMS.2019.2938156

OFS can be characterized as how well a human operator can react to the demands of an operation considering internal and external factors, according to the operator's cognitive and physiological capabilities [10]. OFS is a broad concept, but it can be evaluated under the perspective of three main areas: situation awareness, mental workload, and mental fatigue (MF). MF builds up as an operation progresses and can drastically reduce operators ability to understand, react, and solve problems imposed by the operation quickly, including both common procedures and unexpected situations.

Various methods have emerged of assessing MF. Subjective evaluations include the NASA Task Load Index [11], the Karolinska Sleepiness Scale [12], the Epworth sleepiness scale [13], and the Chalder fatigue scale [14]. While these subjective approaches can achieve good results in assessing MF states, they rely on self-report and are thus subject to bias. More objective methods include monitoring operators performance, such as tracking steering wheel movements or pressure on the acceleration pedal during a drive task [15] and monitoring the operator's behavior, including head position, blinking frequency, and yawning [16]. But monitoring the operator's physiological signals is considered the most reliable way to assess MF, since physiological signals start to change long before any external signs of MF manifest [17]. The physiological signals researchers have used include respiration, electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EOG), and electroencephalogram (EEG).

Although it can achieve high accuracy level, the use of physiological signal for assessing MF can provide some challenges. First, measurement generally requires physical contact between operators and sensors, which can make operators uncomfortable and affect the measured signals [18]. Second, analysis accuracy is very sensitive to the quality of the measured signals. In most cases, these signals are very susceptible to noise and need to be preprocessed in order to provide any useful information. EEG is the most prominent signal in the field today due to its low intrusiveness [19] and its clear relation between the power spectrum characteristics in different frequency bands and MF levels [20]. EEG signals also have other applications in the medical field such as seizure detection and engineering field such as brain–computer interfaces.

The main goal of this survey paper is to provide a comprehensive understanding of the current state-of-the-art techniques regarding the use of EEG to assess MF and how to apply these

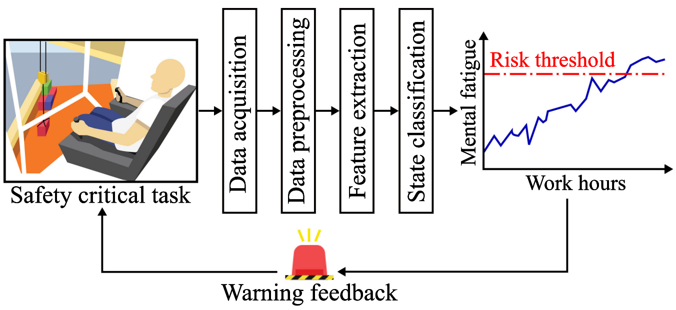


Fig. 1. Closed-loop EEG-based MF assessment framework.

techniques in real-life situations. We seek to understand the current trends in the field in order to present to researchers the newest techniques available and the new knowledge built in this area in the past years.

The rest of the paper unfolds as follows. Section II provides a comprehensive summary of MF assessment pipeline using EEG. Section III describes the methodology used for the literature survey and analysis. Section IV describes the state-of-the-art methods currently available for assessing MF using EEG. In Section V, we discuss the current picture of the EEG for MF assessment research field and provide our vision of a feasible EEG-based MF detection system for implementation in real-life applications. Section VI concludes the paper.

## II. EEG for Metal Fatigue Assessment—Background

### A. Structure of an EEG-Based MF Assessment Method

An EEG-based algorithm that can be used to assess MF must be structured to provide data acquisition, data preprocessing, feature extraction, and MF state classification [21]. Fig. 1 provides an example of the use of this structure in the MF detection framework we propose. EEG data is collected from a crane operator working in an oil rig and preprocessed; features are extracted, and the MF state is classified. The state assessment is used in a threshold algorithm, which closes the loop with the operator with a warning feedback when the MF level exceeds a critical level.

Beyond the basic structure, the methods to handle and classify EEG data need to be specially tailored for specific applications. In addition to the basic underlying structure, new elements can be added to the workflow according to the special needs of each algorithm. For example, applying a dimension reduction technique on the features vector will reduce the classification algorithm input to its more meaningful components [22].

The next sections describe the basic processes present in EEG-based MF assessment methods.

### B. Data Acquisition

During the data acquisition phase, two main aspects govern the acquisition of EEG signals, as described below.

*1) Electrodes Placement:* Jasper [23] created the International 10–20 system in order to standardize the placement of

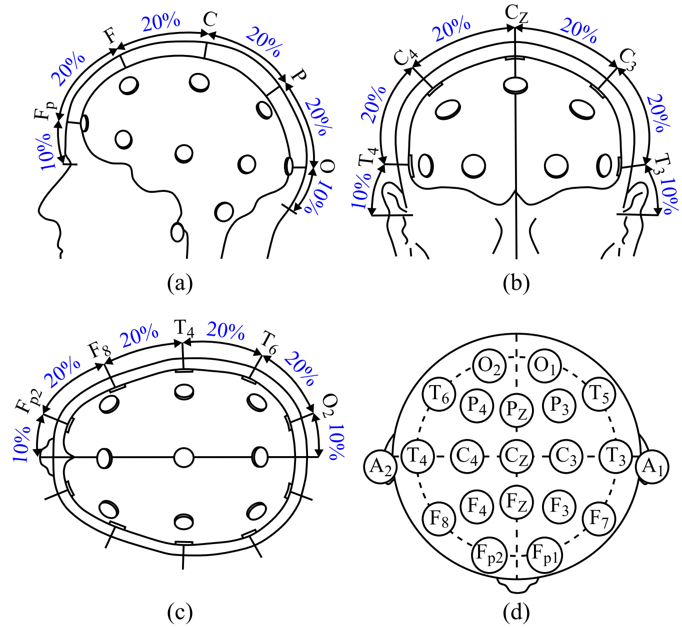


Fig. 2. International 10–20 system definition. (a) Lateral specification. (b) Frontal specification. (c) Superior specification. (d) Electrodes placement and naming. Adapted from [24].

electrodes on the scalp to make the direct comparison of results from different research groups possible.

The naming convention for each electrode is as follows: fronto-polar area (Fp), frontal area (F), central area (C), parietal area (P), occipital area (O), temporal area (T), and auricular electrodes (A). Besides the area names, there is also a numbering convention to help distinguish between left and right homologous regions, using odd numbers for the left hemisphere, even numbers for the right hemisphere, and "$z$" (standing for zero) for the vertex electrodes [24]. The full electrode arrangement is shown in Fig. 2.

The 10–20 system offers 21 positions to place electrodes, which is not enough when using newer EEG hardware that supports 32, 64, 128, or 256 data channels [25]. To account for the increase of data channels, the 10–20 system was expanded to define more standardized position in the scalp for electrode placement. The extended 10–20 system (also called 10–10 system) [26] increases the number of standard positions from 21 to 74. Other extensions have been proposed such as a 10–5 system supporting up to 345 standard positions [27].

*2) Frequency Bands:* EEG signals are composed of a wide range of frequency components. When evaluating EEG signals for MF detection, the range of interest is limited to between 0.3 and 30 Hz. This frequency interval is divided into five main frequency bands (also called rhythms): delta, theta, alpha, beta, and gamma [28].

1) Delta band ($\delta$) corresponds to the interval of 0.3–4 Hz. It represents very slow brain activity, identified in infants up to 1 year or in deep sleep stage in health adults. It is usually not used for MF detection, since it is mostly present in a physiological state outside the interest of MF detection studies.

2) Theta band ($\theta$) corresponds to the interval of 4–8 Hz. It can be found in healthy, alert infants, and children as well as during drowsiness and sleep in adults. Awake, healthy adults have low $\theta$ activity. The frontal $\theta$ activity is likely to increase as a person fatigues [29].
3) Alpha band ($\alpha$) corresponds to the interval of 8–13 Hz. It can be found in healthy awake adults, when relaxed or mentally inactive. The occipital and parietal $\alpha$ activities are likely to increase as a person fatigues [29].
4) Beta band ($\beta$) corresponds to the interval of 13–30 Hz. It signifies tension and anticipation and can be found in alert and anxious subjects. The changes in $\beta$ activity as a person fatigues still unclear [29].
5) Gamma band ($\gamma$) consists of frequencies above 30 Hz. Usually does not have impact on MF detection, being filtered out of the EEG data [30].

### C. Data Preprocessing

EEG signals have very small amplitudes and are highly sensitive to noise. These noises are called artifacts. They are undesirable electrical potentials that come from sources other than the brain [28], such as EOG, EMG, ECG, and power line and amplifier noises, poor electrodes' contact with the scalp and current drift [31]. When present in the data, these noise components make the analysis of the desired phenomena nearly impossible [32], since they may have amplitude in the order of hundreds of $\mu$V [33] and EEG signals are in the order of tens of $\mu$V. Therefore, artifacts need to be detected and removed from the data. Understanding the advantages and limitations of each preprocessing technique is very important in order to choose the right method for each EEG application.

In recent years, the most commonly used preprocessing methods in the field of MF detection using EEG include digital filtering, independent component analysis (ICA), and discrete wavelet transform (DWT).

Digital filtering is very useful to remove noise and artifacts that are frequency-specific, such as body movement and power line noises. Among these filters, we can consider low-pass, high-pass, band-pass, and notch filtering [31]. In ICA, the EEG signal is seen as a linear combination of independent signals. The ICA decomposes the multichannel data into temporal independent and spatially fixed components [34].

DWT is the subset of wavelet transforms that discretely samples the wavelets. The DWT is capable of decomposing a signal in the time domain in a series of wave-like oscillations (wavelets) in different frequency bands. The biggest advantage of wavelet transform approaches for handling time-series data is the fact that they preserve the signal temporal information together with frequency, allowing the analysis of nonstationary data, which Fourier transforms cannot achieve.

### D. Feature Extraction

After preprocessing, the data are more suitable for use in an MF assessment method, but work remains to make it a favorable format to allow classification algorithms to fully explain the represented phenomenon. In order to make the data contained in the EEG signal more meaningful and manageable, relevant features can be extracted. These features basically represent important characteristics of the dataset in a format more compact and easier to handle. Extracting meaningful features from EEG signals is complicated due to its complex, unstable, nonstationary, and nonlinear nature.

In past years, the most commonly used feature extraction methods in the field of MF detection using EEG include power spectral density (PSD), statistics, and entropy measures.

The PSD of a time series describes the power distribution in the signal as a function of frequency [35]. It is especially relevant for EEG classification, since the power in different frequencies can be related to the brain activity in different subbands of interest, making it possible to evaluate changes in the mental state of a subject by tracking changes in the signal PSD. The calculation of PSD is usually preceded by the application of a Fourier transformation in order to change the EEG signal from time to frequency domain.

Statistics can have poor performance when applied as a feature extraction method for EEG signals, since this kind of data is nonstationary by nature. A common way to avoid this problem is to divide the EEG signal in shorter segments and assume the signal is stationary in each of these segments. In this way, statistical analysis can be applied to EEG signals and parameters such as mean, standard deviation, skewness, and kurtosis can be calculated.

Various entropy measure methods have been used to analyze EEG signals [36]–[40] due to its robustness in evaluating the regularity and predictability of complex systems. Entropy was originally used in thermodynamics to assess the degree of disorder in a system, and now it is also used in information theory as a way to measure the uncertainty of systems [41]. As a person gets fatigued, we can expect a decrease in the entropy level of its EEG signals, indicating a decrease and weakening of brain synapses. Recently, the most commonly used entropy measures are sample entropy (SampEn), fuzzy entropy (FuzEn), approximate entropy (AppEn), and spectral entropy (SpecEn).

When the number of features obtained is too big to be directly used in the classification algorithm or when an improvement in the algorithm performance is needed (especially for online application), dimension reduction techniques such as principal component analysis (PCA) and ICA can be applied to obtain an optimized set of features.

### E. MF State Classification

The classification algorithm can classify the input features in any number of classes, depending on how the algorithm is trained or designed to handle the input data. Most of the works use two MF states, but some works consider the existence of intermediate states. These states indicate the transition between the normal and fatigue states.

Among the EEG-based MF assessment methods, no classification algorithm clearly dominates the field. Classification algorithmwise, the state of the art is very heterogeneous, presenting just a few algorithms, which were applied in more than one publication [e.g., Bayesian neural network (BNN),

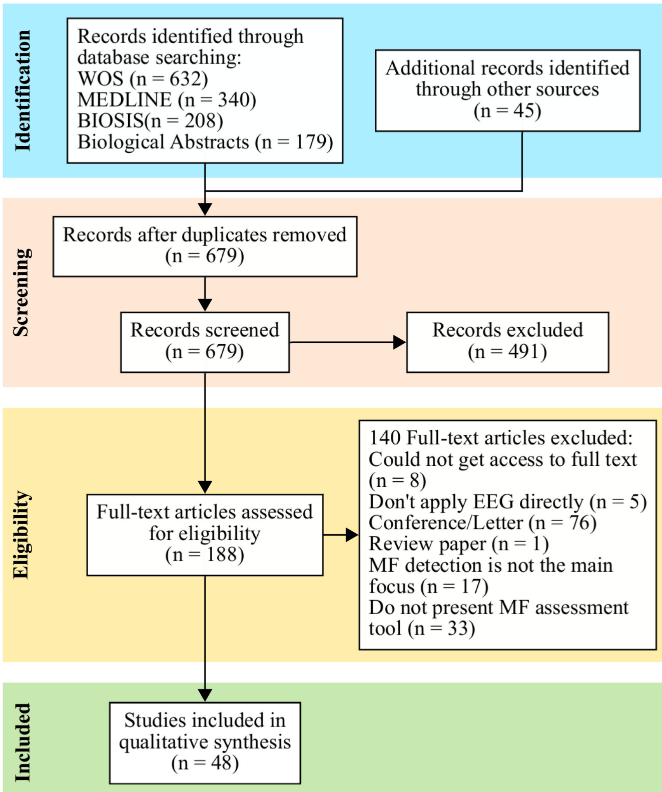


Fig. 3. PRISMA flow diagram.

k-nearest neighbor (kNN), support vector machine (SVM)]. This heterogeneity is due to the fact that no classifier fits all kinds of problems. The best classification tool for each case should be selected based on the particular characteristics of each dataset [42]. The different state-of-the-art classification algorithm will be briefly presented in Section IV.

## III. Methods

In this section, we describe our survey methodology. We first present the literature search methodology using the PRISMA statement and follow up by presenting our classification strategy for the surveyed literature.

### A. Literature Search Approach

This survey paper is structured following the guidelines presented on the PRISMA statement [43]. The process behind the selection of papers for this survey follows the PRISMA flow diagram, presented in Fig. 3. Papers included in the identification phase were those published in English between January 2013 and December 2017 with a title, abstract, or body containing results for the following Boolean search statement: (MF or fatigue) and EEG. The remaining steps of the selection process are depicted in Fig. 3, including all criteria used in the eligibility phase.

### B. Categorization Approach

When describing a method to assess MF using EEG signals, there are some very important characteristics that are relevant to the way it will perform and to how it can be extended to case studies other than the original application. Having a taxonomy describing these characteristics can help researchers to select methods that meet the requirements of their specific problems. Hereafter, we present a taxonomy that highlights the characteristics we consider the most relevant for this kind of application. These characteristics are nonlinearity, nature, dynamics, implementation, and cross subject.

*Nonlinear (N):* Specifies which kind of discriminant algorithms was used in the current MF assessment method to distinguish between different MF states: linear or nonlinear classifier.

*Generative (G):* This refers to how the model handles different classes in the dataset. The method is discriminative if it is only capable of learning how to discriminating between the data in different classes, without explaining its structure. If a method is also capable of explaining how the data in each class is structured, being able to model the data, it is called a generative method.

*Dynamic (D):* Specifies if the MF assessment method uses temporal information during classification. This requires that the method is capable of storing a significant amount of past information to use in the classification task at each instant. If the method can keep track of temporal information, it is said to be dynamic; if not is it said to be static.

*Online (O):* A method may be implemented offline or online. Offline implies that the method stores information for later classification (i.e., not real time). Online means the MF assessment is made in real time.

*Cross Subject (C).* We say a method is considered cross-subject influence, if it explicitly took into consideration the individual physiological characteristics of each subject in the classification process. This is an important factor to consider, since MF limits and their representation in physiological signals can differ across subjects.

Besides the taxonomic decomposition of the state of the art described above, we also classified the surveyed papers according to the data processing pipeline presented in Section II by identifying the chosen approaches for data preprocessing, feature extraction, and classification algorithm. The results of this classification approach are presented in Section IV and are summarized in Tables I–III.

All the surveyed papers are reported according to the data domain, where the EEG data were analyzed during the MF assessment task. In each data domain table, papers are compared regarding the main characteristics of the MF assessment pipeline described in Section II, namely preprocessing, feature extraction, and classification algorithm, and the taxonomy presented in Section III. For the sake of a cleaner presentation, the taxonomy terms are represented by their initials in Tables I–III. The presence of a check mark in a taxonomy field indicates that the paper presents that desired characteristic.

Additionally, although the classification accuracy obtained by the authors in each paper is presented in these tables, they

TABLE I
TIME DOMAIN METHODS

| Preprocessing | Feature extraction | Classification algorithm | N | G | D | O | C | Acc. | Ref. |
|---|---|---|---|---|---|---|---|---|---|
| Band-pass filter | Statistics | SDAR | ✓ | ✓ | ✓ | ✓ | | 95% | [58] |
| | PCA | OwARR, OwARR-SDS | ✓ | | | ✓ | ✓ | - | [56] |
| | SamEn, FuzEn, AppEn, SpecEn | AdaBoost | ✓ | | | | | 97.5% | [55] |
| | | DT | ✓ | | | | | 95.7% | [54] |
| | SamEn, FuzEn, AppEn, SpecEn / Fisher distance | SVM | ✓ | | | | | 98.8% | [53] |
| | Fuzzy Entropy / Fisher distance | SVM | | | | | | 85% | [52] |
| Band-pass filter, Notch filter | SamEn, FuzEn, AppEn, SpecEn | MLP | ✓ | | | | | 98% | [46] |
| | | RF | ✓ | | | ✓ | ✓ | 96.6% | [47] |
| Band-pass filter, Visual inspection | DNTF | SVM | ✓ | | | | ✓ | 98% | [51] |
| ICA | AR modeling | BNN | ✓ | | | | | 88.2% | [48] |
| | | Sparse-DBN | ✓ | ✓ | | | | 93.1% | [49] |
| | Statistics | Dynamic-BNN | ✓ | | ✓ | ✓ | | 95% | [50] |
| - | Meditation and Attention EEG | k-NN | ✓ | | | | | 83.6% | [57] |

TABLE II
FREQUENCY DOMAIN METHODS

| Preprocessing | Feature extraction | Classification algorithm | N | G | D | O | C | Acc. | Ref. |
|---|---|---|---|---|---|---|---|---|---|
| Band-pass filter | PSD | SVM | | | | ✓ | | 98.2% | [74] |
| | | SVM | | | | ✓ | | 96.2% | [75] |
| | | RBF-SVR | ✓ | | | ✓ | | - | [78] |
| | | RSEFNN | ✓ | | ✓ | ✓ | ✓ | - | [79] |
| Band-pass filter, Coherence method | PSD | ABSVM | ✓ | | | ✓ | ✓ | 82.2% | [77] |
| Band-pass filter, Coherence method, ICA | PSD / Statistics | SDBN | ✓ | ✓ | | ✓ | ✓ | 77% | [59] |
| Band-pass filter, Notch filter, ICA | PSD | FLDA | | | ✓ | | ✓ | 80% | [60] |
| Band-pass filter, Visual inspection, ICA | PSD | Thresholding | | | | ✓ | ✓ | 76% | [61] |
| Band-pass filter, ICA | PSD | SDAE | ✓ | ✓ | | ✓ | ✓ | 85.6% | [62] |
| | PDC | SVM | ✓ | | | | | 81.5% | [63] |
| ICA | FFT / NWFE | SVM | ✓ | | | | | 88.7% | [64] |
| | | RBFNN | ✓ | | | ✓ | ✓ | 91.6% | [65] |
| | SPD / Statistics / SVM | SVM | ✓ | | | | ✓ | 75% | [66] |
| Low-pass filter, PCA | PSD | SVM | ✓ | | | ✓ | ✓ | 80.4% | [67] |
| PCA | PSD | SVM | | | | | | 94% | [68] |
| De-noising wavelet | PSD | KPLS-DLR | | | ✓ | ✓ | ✓ | 97% | [69] |
| | | Sparse-KSVD | | | | ✓ | | 95% | [70] |
| DWT | PSD | SVM | ✓ | | | ✓ | | 90.7% | [71] |
| Fisher bilateral test | PSD | Thresholding | | | | | | 98.3% | [72] |
| - | PSD | SVM | ✓ | | | | | 86% | [76] |
| | | temporal aggregation SVM | ✓ | | ✓ | ✓ | ✓ | 87% | [73] |

should be analyzed with caution. Since most researchers in the field do not make use of benchmark datasets, it is not possible to compare the accuracy of different studies reliably. As an example, a case study that considers cross-subject classification is expected to have a lower classification accuracy than one that only considers single-subject classification. Publications presented in this survey without accuracy value use regression methods, and performance is evaluated by root-mean-square error instead of accuracy.

## IV. STATE OF THE ART OF MF ASSESSMENT USING EEG

EEG data can be processed in different domains, including PCA and ICA [44]. In the present work, we divided the MF assessment method according to the three main data domains, namely time, frequency, and time–frequency.

EEG signals are obtained as time series, which are noisy, high dimensional, and nonstationary, have an explicit dependency on the time variable, and require the extraction of features from them to be invariant to translations in time [45]. So, although the natural domain of EEG is time, all the previously cited signal characteristics can make the analysis of data in the original domain quite challenging. Also, the EEG signals have clinical significance in different frequency bands ($\delta$, $\theta$, $\alpha$, and $\beta$), which cannot be observed directly in the time domain.

To overcome these issues, some researchers opt to evaluate the EEG data in the frequency domain. This approach makes it possible to visualize the important frequency bands and avoid the problematic characteristics of time-series signals. The

TABLE III
TIME–FREQUENCY DOMAIN METHODS

| Preprocessing | Feature extraction | Classification algorithm | N | G | D | O | C | Acc. | Ref. |
|---|---|---|---|---|---|---|---|---|---|
| Band-pass filter | Raw data, ICA | CCNN, CCNN-R | ✓ | | | ✓ | ✓ | 76.7% | [90] |
| | WPT / Statistics / MI | SVM | ✓ | | | ✓ | | 98.6% | [91] |
| | DEn | SVR | ✓ | | ✓ | | | 85% | [89] |
| Band-pass filter, Notch filter | EMD | MLP | ✓ | | | | ✓ | 84.5% | [92] |
| | DWT | Thresholding | | | | ✓ | | 85% | [93] |
| Band-pass filter, Visual inspection | Statistics, SamEn, PSD | SVM | ✓ | | | | ✓ | 80% | [81] |
| | KC / AppEn / PCA | SVM | ✓ | | | | | 85% | [82] |
| Band-pass filter, Adaptive filter | Statistics / LDA | MLP | ✓ | | | ✓ | | 85.7% | [80] |
| Visual inspection | SamEn, AppEn, RenyiEn, RQA | ELM | ✓ | | | ✓ | | 97.3% | [83] |
| DWT | WEn | PCNN | ✓ | | | ✓ | | 97% | [86] |
| | Best m-term approximation | Thresholding | | | | ✓ | | 98.7% | [87] |
| | Statistics | deep-LSTM | ✓ | | ✓ | | | 93% | [88] |
| | WEnS, PP-ApEnS, PP-SampEnS | MLP | ✓ | | | ✓ | | 96.5% | [84] |
| WPT | PSD | Thresholding | | | | ✓ | | - | [85] |

time–frequency domain is another option that merges time and frequency domain characteristics by decomposing the original time series into one time series for each desired frequency band. This approach conserves the temporal characteristics of the original EEG signal, which can be valuable for certain assessment methods. The following sections discuss EEG-based MF assessment methods in each of these three domains.

### A. Time Domain Methods

*1) Preprocessing:* Most time domain methods rely heavily on digital filtering as the main preprocessing approach. Band-pass filters are used to restrict the EEG signals to the frequency intervals of interest for MF analysis. Notch filters are applied to remove specific noise from the data, such as powerline noise [46], [47]. In order to remove blink, heart, and muscle artifacts from EEG data, ICA [48]–[50] and visual inspection [51] are also applied.

*2) Feature Extraction:* Several different types of entropy measures have been applied for feature extraction in the time domain. Entropy measures are popular due to the ability to measure the degree of uncertainty in unstable and nonlinear time series such as EEG signals. These measures can be used to compare normal and unsettled brain states. In some cases, different entropy measures are used in isolation [47], [52], but they can also be combined in order to improve the quality of extracted features [46], [53]–[55].

Complex EEG data from several channels can be represented in a simpler way by means of PCA, transforming the original set of inputs to a new set of coordinate systems that encapsulates the greatest amount of the original variance in the least number of new components as possible [56]. Alternatively, the complex input data can be factored using nonnegative decomposition methods, which factor the input data in meaningful components without applying any transformations to it [51].

An alternative for spectral analysis in the time domain is autoregressive (AR) modeling. It has been applied due to its ability to model the peak spectra of EEG signals and reportedly provides a better set of features then fast Fourier transform (FFT)-based methods [48], [49].

*3) Classification:* SVM is used as classifier for MF assessment problems, since it can group input elements in different classes. It is a kernel-based method, meaning that it can perform different linear [52] and nonlinear classifications [51], [53] by just changing its kernel function. Another algorithm that makes use of clustering is kNN. When kNN is used for a classification task, an input element is classified by a majority vote of its kNNs, where its class is assigned as the most common one among these neighbors [57].

Decision tree (DT) is a predictive model, where the branches and leaves structure represent, respectively, the classes features and labels. Thus, a label is represented by the conjunction of features that lead to it. It is a simple model capable of modeling large datasets with little data preparation well. When combined with boosting, it can perform well on noise datasets [54].

The main disadvantage of DT is its tendency to overfit to the training data. Random forest overcomes this flaw. It is an ensemble method that considers several DTs for the classification task. This approach provides a set of more robust features for training the classifier [47]. AdaBoost is another ensemble classification method, which weighs the classification results of multiple other classifiers and makes a decision based on the majority voting criteria. Hu [55] applied AdaBoost with SVM, DT, and Naive Bayes subclassifiers.

Neural networks are extensively used for MF assessment in time series, since different network structures can provide interesting properties to the classification algorithm. Good classification results can be obtained using all kinds of neural networks, depending on the specific necessities of each dataset. Even a simple and not very robust model, such as the multilayer perceptron (MLP), can achieve good classification accuracies if trained properly [46].

One of the crucial issues when using a neural network approach is to ensure that the learned structure can make a good generalization when data never seen before is presented to it. Chai *et al.* [48] propose the use of BNN as a classifier due to its ability to generalize the data analysis independently of how small or noisy the dataset is.

A neural network can learn very intricate features from the input data, including how the data structure is composed. One example of such a model is a deep belief network (DBN), which is a nonlinear classification model composed of an unsupervised generative model and a supervised discriminative model. The model can be made more efficient by adding sparsity to the network, preventing it from over-fitting [49]. Some neural network models can also learn how to model temporal relationships of state variables, making the classification algorithm dynamic [50].

Besides classification, a regression approach can also be applied for MF detection. A sequential discounted autoregressive (SDAR) model of order $N$ sequentially represents each data point in a time series as a combination of $N$ previous point, with a discount factor for older points. When using statistical features, such a model can be trained to predict changes in EEG data with timing precision close to 150 ms [58]. Regression models can also be used for accounting for EEG differences among multiple subjects. Online weighted adaptation regularization for regression (OwARR) achieves this by online fusing data from old and new subjects, constantly adapting the classification model. Source domain selection (SDS) is applied to reduce the number of previous subjects needed to estimate new regression for real-time applications [56].

Table I presents the discussed time domain methods, comparing their main characteristics.

### B. Frequency Domain Methods

*1) Preprocessing:* On the frequency domain, the preprocessing phase receives special attention from researchers. Besides the more common digital filters like bandpass and notch filters, specialized algorithms are frequently used for artifact rejection. Slow artifact rejection are especially relevant on frequency domain analysis, since they have a big impact in the spectral powers of $\delta$, $\theta$, $\alpha$, and $\beta$ subbands.

ICA is the most popular choice due to its simplicity and efficacy in rejecting EOG and movement artifacts [59]–[66]. It decomposes the original signal into independent components that can be inspected in order to reject the ones related to artifacts.

Other approaches similar to ICA present in the surveyed literature are PCA [67], [68] and denoising wavelets [69]–[71]. Both approaches consist of decomposing the original signal in a new set of components (principal components and subband intervals, respectively) and rejecting the components closely related to EOG, ECG, and movement artifacts. The Fisher bilateral test was applied as a thresholding method for artifact rejection [72]. In this case, the EEG data is compared to a 60-s long reference signal known to be artifact free.

*2) Feature Extraction:* By far the most common approach to feature extraction on the frequency domain is spectral analysis through FFT and PSD. Researchers are not only interested in the spectral powers for $\delta$, $\theta$, $\alpha$, and $\beta$ subbands, but also in the relation and ratios among these frequency bands, since they carry important information about MF state changes. Additionally, the ratios between spectral powers of different frequency bands help the classification model to account for cross-subject variations in the input data [60], [61], [72], [73].

In the literature, statistics are also applied together with spectral analysis for feature extraction. They can be fed to a classifier directly [59] or filtered by some kind of feature selection algorithm [66]. Nonparametric feature extraction was also applied due to the advantages of parametric models, such as better performance for nonnormal distributed data [64], [65].

*3) Classification:* Since most of the feature extraction methods on frequency domain rely on discrete spectral features, there is a large number of linear classifiers in the surveyed literature. The most common linear classifiers are SVM with linear kernel functions [68], [74], [75] and simple thresholding [61], [72]. Kernel partial least squares (KPLS) decomposition was used on the EEG data to find and select a reduced set of orthogonal components with maximum covariance. It was coupled with discrete-output linear regression (DLR) classifier to define a linear hyperplane capable of separating the MF states in the appropriate classes [69].

Yet in the realm of linear methods, k-singular value decomposition (KSVD) was applied to generate an overcomplete dictionary of signals that can be used to, sparsely, represent the input signal as a linear combination of the learnt signals [70]. Also, Fisher's linear discriminant analysis (FLDA) was used to find a linear combination of features that characterizes different MF states. This set of features can be applied as a linear classifier [60].

SVM is the most common method used for MF classification in the frequency domain. Besides its use with linear kernels, it was also extensively applied with nonlinear kernels, for more robust classification performance [63], [64], [66], [67], [71], [76]. Some more specialized versions of the traditional SVM algorithm were also used. Temporal aggregation SVM was applied in order to make the SVM algorithm dynamic [73]. Adaptive bounded SVM (ABSVM) can be used for two reasons: the bounded part optimizes the SVM training procedure when more than two MF states are considered and the adaptive part optimizes the results for cross-section and cross-subject classification problems [77]. Support vector regression (SVR) is a variation of SVM that performs regression instead of classification and was used to create an MF predictor [78].

Neural network models were also found in the surveyed literature. Sparse DBN [59] and sparse deep auto encoders [62] were used to create generative models capable of accounting for, respectively, cross-subject and cross-session variability. Radial basis function neural network (RBFNN) is basically an MLP with exactly one hidden layer and uses radial basis functions as activation functions. It was applied to construct a nonlinear MF state classifier due to its training and classification performances [65]. A recurrent self-evolving fuzzy neural network (RSEFNN) was used to create a dynamic regression tool capable of accounting for cross-subject regression of MF states [79].

Table II presents the discussed frequency domain methods, comparing their main characteristics.

### C. Time–Frequency Domain Methods

*1) Preprocessing:* Researchers typically focus on two approaches to the preprocessing phase in the time–frequency domain: digital filtering and wavelets. As seen in the previous section, bandpass and notch filters are largely used as noise and artifact removal tools. Adaptive filters are also viable digital options for noise and artifact rejection [80]. Experts also use visual inspection to remove artifacts [81], [82]. This approach is especially effective when relying on data from other sensors, such as EMG and EOG [83].

Wavelet transforms will decompose a time series into a set of components with different frequency bands. They are effective for analyzing nonstationary signals, since they can represent trends, discontinuities, and patterns in the original signal very well [84]. Wavelet packet transform (WPT) is the simplest wavelet transform, disregarding boundary treatments in the original signal [85]. DWTs are most commonly used due to their more robust performance [86]–[88].

*2) Feature Extraction:* One of the reasons to conduct EEG analysis in the time–frequency domain is to work with nonlinear features for the MF state classification. Usually, authors opt for different entropy and complexity measures to capture the nonstationarity and nonlinearity of EEG signals. The separation of the original signal in its main subbands seems to improve the nonlinear features performance. Some of the applied measures include differential entropy (DEn) [89], AppEn, SampEn, Renyi entropy (RenEn), recurrence quantification analysis (RQA) [83], wavelet entropy (WEn) [86], and Kolmogorov complexity (KC) [90]. The use of sliding windows for the calculation of entropy measures can be applied for real-time MF detection [84].

When working on the time–frequency domain, most authors opt to use some type of wavelet transformation to convert the EEG time series to the time–frequency domain. When doing this, da Silveira *et al.* [87] used best *m*-term approximation to select the wavelet decomposition terms with the biggest influence in alpha and beta subbands. Kaur and Singh [92] opted for a different approach to make the EEG data domain transition. They applied the empirical mode decomposition method (EMD) to extract intrinsic mode functions from EEG signals.

Instead of focusing the MF detection method on only one domain, some authors try to expand their possibilities by transitioning between different domains during the EEG data analysis. Correa *et al.* [80] made use of statistical features in the time, frequency, and time–frequency domain to assess drivers drowsiness state. Lee *et al.* [91] extracted 51 statistical, frequency, and interval features from EEG and respiration signals, and performed feature selection using mutual information (MI).

Since time–frequency domain signals contain all frequency domain information available, the use of spectral analyzing on the decomposed signals by deriving power-based indices is still a viable option [85].

*3) Classification:* Most of the works surveyed on the time–frequency domain use some sort of entropy, complexity, or statistical measures as features. Therefore, the classification algorithms need to distinguish among different MF states based on a set of discrete measures. Three approaches to this task dominate thresholding, SVM, and neural networks.

Thresholding classifiers are the simplest. They are trained to find the limits for the features that define each MF state. They are mostly linear and were used on spectral features [85] and

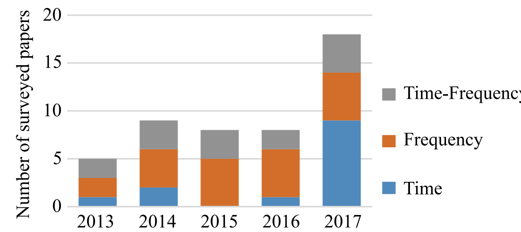


Fig. 4. Number of surveyed papers per year and domain.

on the decomposed time series [87], [93]. As in the frequency domain, SVM is extensively applied as a clustering method, to group the input signals in different MF state classes based on nonlinear features. Only nonlinear kernels were used for SVM in the surveyed works [81], [82], [91]. SVR was also used together with a continuous conditional neural field and a continuous conditional random field to produce a dynamic estimator of the MF state [89].

One of the most simple neural network models is called single layer perceptron (SLP). Although SLP is not very useful for complex classification problems by itself, a variation of SLP called extreme learning machine (ELM) was successfully applied for MF state classification due to its ability to avoid local optima and fast training speed [83]. An MLP classifier was used in several works with good results [80], [84], [92] although more complex and robust neural network model was also used. Deep long short-term memory (LSTM) was used to construct a dynamic classifier to account for the fact that MF has a very important temporal factor, since it builds up over time [88]. Channelwise, a convolutional neural network (CNN) was used to automatically extract a complex feature from time-series data [90]. Such features are robust enough to provide effective cross-subject classification of the MF state.

Table III presents the discussed wavelet domain methods, comparing their main characteristics.

## V. Discussion and Future Trends

The number of published works using EEG to assess MF has steadily increased in the recent years, as shown in Fig. 4. This increase reflects a change of paradigm in human–machine systems as machinery systems become increasingly reliable and consequently human operators account for a steady increase in accidents. This increase also shows that higher levels of automation in several industries, such as automotive [94] and maritime [95], have not made the topic less relevant. This is because in most cases automation does not remove the human element completely from the loop, but just reallocates it to a different role.

Fig. 4 also shows a big shift regarding the data domains used for analyzing the EEG data. The time domain, which was barely used in previous years, came to dominate in 2017. This most likely indicates the development of methods capable of dealing with time series and its particularities. including nonlinearity, high levels of noise, high dimensionality, and nonstationarity [45]). Some methods capable of dealing with these special

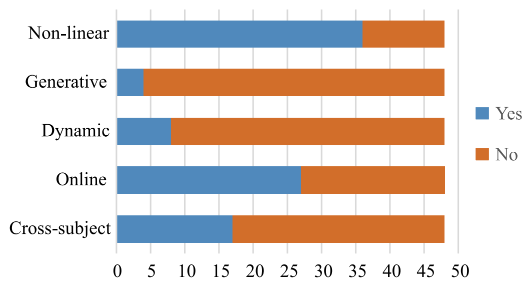


Fig. 5. Taxonomy distribution for the state of the art.

requirements from time series include deep learning methods, such as CNN, DBN, and auto encoders.

An overview of the taxonomic distribution can be seen in Fig. 5. Most of the taxonomic characteristics have an undeniable tendency across the field, which may indicate either a conformation about how the MF assessment methods should be structured or a possible turning point for further improvement. We can see that the vast majority of the papers applied nonlinear methods for handling EEG data. This is expected, since measuring linear features that can correctly represent time-series data can be very tricky, due to the intrinsic nature of this kind of signal. The greatest number of papers also use a discriminative approach, since most generative models are deep-learning based, and this kind of architecture has not been much explored in the field of MF assessment with EEG, although as noted there has been a shift toward deeper models. Regarding the dynamics, most papers use a static approach, since keeping track of temporal data to assess the MF state is demanding, especially for real-time applications. With the development of models such as LSTM, a dynamic approach is becoming more feasible, which is very relevant, since the MF state is a built-up process, where the tiredness accumulates over time, making this temporal dependency very relevant for an accurate analysis. The cross-subject aspect was evaluated by few researchers, although it is known that the EEG signals and MF state are subject-dependent, presenting variation among people. Future research should address this point. Regarding implementation, fortunately, almost 50% of the published work in the past five years presented methods capable of being implemented in real time, which is essential for real-life application. Usually this kind of online method uses little to no preprocessing, a simpler set of features, and a small amount of EEG channels in order to reduce the computational requirement and hardware footprint as much as possible.

The application areas where MF detection using EEG has been applied are driving, mental load tasks [51], [63], [68], [69], [82], [83], [88], safety-critical tasks [59], [62], [77], train piloting [71], and aircraft piloting [72]. Fig. 6 shows that driving tasks dominate as a case study for most of the published work. This reflects the automotive industry's efforts to provide systems to detect drowsiness in drivers, which have been implemented by several automobile manufacturers, including Audi, Volkswagen, Volvo, BMW, and Mercedes-Benz. Most of the systems available

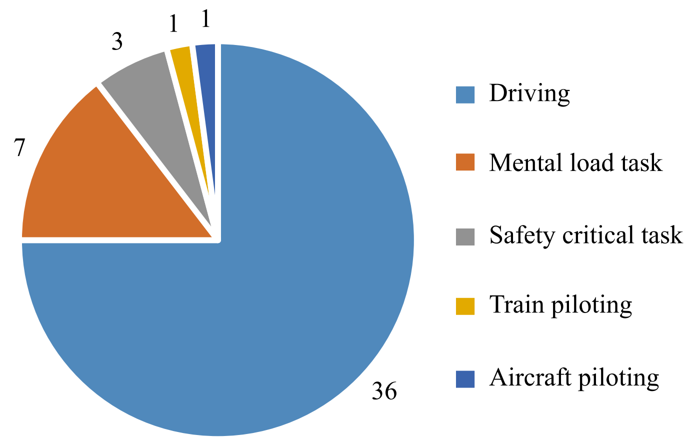


Fig. 6. Application areas distribution for the state of the art.

today use driving patterns, such as steering pattern, vehicle lane positioning, and acceleration and brake pattern [96] to identify fatigued drivers. Although some systems use driver's eyes and face monitoring to assess drowsiness [97], no commercial system the car industry has employed currently applies physiological signals to detect MF. Implementing a system that monitors physiological signals that can be used in real-life applications for detecting MF is the next step in accident avoidance in human–machine systems, and the automotive industry seems to be the most likely to achieve this first. Although other fields need such systems, minimal effort has been put into developing them, which provides an opportunity for researchers in other areas to develop new methods and tools for real-time MF detection.

### A. *Feasibility of EEG-Based MF Detection Systems*

Several EEG-based MF detection methods can achieve classification accuracy over 90%. Although impressive, these numbers hide important limitations of current approaches that make the transition from research laboratories to real-life applications very difficult. These important points to consider are discussed below.

*1) Cross-Subject and Cross-Session MF Detection:* EEG signals are very sensitive electrical signals and can behave differently from person to person, so MF detection methods need to be robust enough to handle these variations. This robustness is also necessary to ensure a good generalization capability needed to handle subjects outside the training samples. On the surveyed literature, cross-subject and cross-session variability is most commonly approached in the frequency domain. The advantage of frequency domain methods is the use of spectral power ratios, which help to compensate for different ranges of theta, alpha, and beta subband activities in different individuals. Some entropy [47], regression [56], and neural network [90], [92] based methods were attempted on time and time–frequency domains, usually with similar accuracy ratios to frequency domain methods.

*2) Computational Requirements:* The process of MF assessment should be as time and energy efficient as possible. It should not rely on expensive computations that require a powerful computer to complete. Basically, any of the surveyed methods that can be considered online present a reasonable level of computational requirement for real-life implementation. Usually the time-consuming part of these algorithms is the training phase, but once the algorithm is trained, its application to new data is fast.

*3) Portability:* The hardware carrying the MF assessment algorithm should be as compact as possible. It should be portable, allowing the user to move around with no restrictions while providing long periods of battery autonomy. On the surveyed literature, portability is achieved using the Android platform [57], [75], [78], [91]. Computationally light MF assessment algorithms are implemented on mobile devices, receiving EEG data in real time via Bluetooth communication.

*4) Intrusiveness:* The MF assessment system should be as nonintrusive as possible so as not to interfere in any way with the performance of the user. If not properly designed, the system can cause distress to the operation. A main factor to improve is the number of electrodes used to acquire the EEG signal, balancing the tradeoff between number of electrodes and precision of MF detection. In the surveyed literature, we considered nonintrusive algorithms that rely on only EEG sensor and consider just few channels. In several studies, authors investigated the use of the simplest possible model, using only one EEG channel [47], [73], [74], [80], [85], [87], making the installation of electrodes as fast and simple as possible and reducing a lot of the computational requirements.

*5) Number of MF States:* MF develops as an accumulative process. Most published works use only two MF states to assess MF. The use of intermediate states between "no fatigue" and "fatigue" can help with the correct assessment of MF, since more gradual change between states can ensure better accuracy and greater response time for safety–critical systems. On the surveyed literature, few authors explored the use of intermediate MF states. We can identify the studies using three [59], [76], [89] or four [67], [77], [91] different MF states. Some methods capable of performing regression can present an almost continuous MF development output [78], [79].

*6) Closed-Loop System:* The assessment of MF is as important as what the system does with this information. There is a need to develop efficient ways to mitigate the effects of MF and to alert the user about the dangers in the operation during the MF state. The MF detection system needs to be capable of acting before any accident happens, in a preventive way. On the surveyed literature, several authors implemented closed-loop systems, but almost all of them used driving as a case study. In most cases, the fatigue threshold detection module sends a sonorous or visual warning feedback to alert the user about dangerous driving conditions [66], [67], [75], [78], [86], [91], [93]. A vehicle speed control model based on an MF assessment algorithm was successfully implemented in [70]. There was only one work that considered a closed-loop system in an application area other than driving, where the author implemented an MF warning feedback for train pilots using sonorous alarm and a massage chair [71].

## VI. Conclusion

Following the continuous increase in quality of hardware and software present in all kinds of machine systems, the role of the human factor and human failure in accidents in human–machine systems has become more evident. One of the biggest causes of human failure lies in excessive MF, which can lead to drowsiness, lack of situational awareness, and slower response to external stimulus. When developing a system that can assess MF and warn the human operator about its critical condition, the use of EEG is recognized as the most reliable way to implement such a system.

This survey paper reviewed the current state of the art of the field of EEG-based MF detection systems. The fundamentals of data acquisition and interpretation were approached. The underlying structure of a typical EEG-based MF detection method was discussed and the most common preprocessing, feature extraction, and classification algorithms were presented and briefly discussed. The main goal of this paper is to provide an overview of the current trends in the area. To do this, we tried very hard to be inclusive of relevant papers published in the past five years. In this review, we discussed these papers' approaches, characteristics, and results based on their application domains, which we divided into time, frequency, and time–frequency domains.

In the final portion of the paper, we discussed the current state of the art using the presented taxonomy as a basis for discussion. The main points of the MF detection methods architectures were approached, and their current usage and future trends were briefly evaluated. There is a lot of opportunity to develop MF detection systems for applications other than driving, and now might be the right moment to put more emphasis into deep learning models that have been barely used to date, always keeping in mind the important role of online models in making real-world applications feasible.

Finally, from our survey study, we recommend the reader to take a closer look at Trejo *et al.* [69]. In this work, the authors implemented an MF detection model based on KPLS-DLR that meets most of the desired criteria for a feasible MF detection system in real life. Their model is dynamic, feasible for online implementation, and robust for cross-subject classification. The system is very minimally intrusive, using only two EEG channels and two EOG channels for artifact rejection. The mathematical algorithm implemented is simple but has outstanding performance (97% accuracy).

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