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# Preliminary Experimental Assessment of an IoT-Based Fatigue Monitoring System for Industrial Operators

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*Abstract* – **Operators' well-being is essential to implement the Industry 5.0 framework. To this end, this paper presents the first experimental results of a wearable IoT system for monitoring the muscle fatigue of operators on assembly lines. The system is completely modular and composed of 4 subsystems: i) a system for the acquisition of physiological signals, an IMU-based system for the acquisition of inertial data, an RFID glove for tag recognition, and an Indoor Positioning System for the evaluation of operators' movement. For each task, operators can express a fatigue rating from 1 to 5, and a bagged decision tree classifier was used for the classification of muscle fatigue. From the results obtained, it is possible to note that the model can predict muscle fatigue with an accuracy higher than 90%.**

## I. INTRODUCTION

In recent years, we have been experiencing a new industrial revolution that will lead to what the experts call the Industry 5.0 paradigm. It is build on the foundation laid by Industry 4.0, which was focused on automation, data exchange, and smart technologies, such as the Internet of Things (IoT), artificial intelligence (AI), and cyber-physical systems, but with the the aim of bringing the human element back to the center of industrial processes [1]. At its core, Industry 5.0 emphasizes collaboration between humans and machines. This paradigm shift aims to combine the efficiency and precision of automation with human creativity, critical thinking, and emotional intelligence, where the human workers work alongside advanced technologies, rather than replacing them [2]. The implementation of Industry 5.0 necessitates several key components: (i) the development of a human-centric system, (ii) the integration of collaborative robots (cobots), (iii) the adoption of flexible production processes that emphasize customization and adaptability, (iv) the deployment of systems designed to enhance operator safety and well-being, and (v) the incorporation of sustainable and environmentally conscious practices. For example, in [3], the authors proposed a wireless sensor network designed for the safety and health monitoring of workers. The system comprises two categories of sensors: (i) a safety node, which monitors environmental parameters such as temperature, relative humidity, ultraviolet radiation, and carbon dioxide concentration; and (ii) a wearable health node that measures physiological indicators including body temperature and heart rate (HR) through PhotoPlethysmoGraphy (PPG). Similarly, the study presented in [4] introduces a monocular vision-based system for recognizing worker postures during construction activities. These studies primarily focus on monitoring either environmental and physiological parameters or ergonomic aspects. However, the physiological parameters monitored, specifically HR and body temperature, are insufficient for estimating an operator's physical fatigue, which is typically assessed using surface electromyography (sEMG) [5]. Fatigue estimation is of particular importance, as it can be used to evaluate risk indices (among which the most used are the EAWS indices [6]), which are fundamental for the physical well-being of operators. Thanks to them, it is possible to identify critical issues in the manufacturing process, which can then be customized to the physical needs of the operator. Moreover, the use of a monocular camera is inherently constrained by its limited field of view, rendering it unsuitable for dynamic assembly tasks in confined or obstructed workspaces where operator mobility is required. To achieve these objectives, one promising approach that has attracted growing attention in both scientific and industrial domains in recent years involves wearable IoT devices [7, 8] used to evaluate fatigue, stress, ergonomic index [5] and postures[7]. In this paper, a system for the automatic classification of operators' fatigue on an assembly line has been developed. Wearable sensors worn by operators during a normal pump assembly shift have been used. In particular, the ECG signal and 3 sEMG signals are acquired in correspondence with the forearm, trapezius, and erector spinae muscles, a BITalino acquisition board, placed on the operator's belt. 3 IMUs with bands are also used to monitor the quaternions of the dominant hand, non-dominant hand and the back. The fatigue declaration is performed after each task, through an RFID glove, with the possibility of giving a qualitative fatigue rating ranging from 1 to 5 (1 being almost no fatigue and 5 being exhausted). Time and frequency domain features are calculated on the acquired signals and used to train a bagged tree ML algorithm for the automatic fatigue assessment. The rest of the paper is structured as follows. In Section 2, a brief review of the state-of-the-art on automatic fatigue classification is presented. In Section 3, a description of the proposed monitoring system is reported. A preliminary experimental campaign is presented in Section 4. Section 5 draws the main conclusions and several future work directions.

## II. RELATED WORKS

In order to assess the well-being of operators, is essential to study how the state of the art deals with fatigue classification. This classification is very important since it is directly correlated to risk indices and to the well-being of operators. The customization proposed by Industry 5.0 should be based on these indices and, therefore, it depends on the perceived fatigue in the various tasks that the operators have to perform. In [9], the authors investigate how a commercially available wearable low-cost sensor and two machine learning algorithms can be applied to measure and evaluate heart rate, heart rate variability and respiration rate to establish a relationship with workload. The sensors used consist of a sensor shirt, a sensor belt and a multifunctional sensor module, and 6 male healthy subjects were used in the experimental evaluation. Furthermore, the RR is used but exclusively for the training of the two chosen Machine Learning models: Random Forest and K-Nearest Neighbors. The task recognition accuracy proposed are very high, around 90-95%. Even if these results are performed on few tasks, and not in an industrial environment, they highlight the possibility of using WHD for task recognition and the correlation between physical stress and fatigue.

In [10], the authors attempted to characterize the nonlinear variations in sEMG measurements and to detect fatigue for the associated activities. The experimental evaluation was conducted on 52 healthy individuals performed repetitive contractions of the biceps muscle and the sEMG signal was recorded. The signals are then codified into a binary sequence and symbolic transition networks were created to model the dynamics of the sEMG signals. From these networks, metrics such as symbolic entropy, network entropy, uniformity, and effective degrees (minimum and maximum) were derived and fed into a classifier (k-Nearest Neighbor or Naive Bayes) achieving a maximum accuracy of 90 %. The study demonstrates that analyzing sEMG signals is effective in detecting muscle fatigue since a significant decrease in signal complexity was observed as muscle fatigue progressed. In [11] the authors performed extensive research to monitor and predict physical fatigue among manufacturing workers using wearable technology and machine learning. The main objective was to develop a system that can continuously monitor and predict varying levels of physical fatigue in real-time, moving beyond traditional binary fatigue assessments. Data were collected from 43 individuals performing two manufacturing tasks: composite sheet layup and wire harnessing and six wearable sensors were strategically placed on the upper body to capture vital signs (heart rate, heart rate variability, skin temperature) and movement data (via inertial motion units). The fatigue level was self-reported by the participants and recorded alongside sensor data during task performance. To perform the automatic classification, a gradient-boosted tree-based regression model with a custom asymmetric loss function was developed to predict continuous fatigue levels, emphasizing accurate predictions of higher fatigue states. The system effectively predicted multilevel fatigue states in real-time, demonstrating its potential applicability in actual manufacturing settings. From the analysis of the state of the art, it is therefore possible to deduce that using features extracted from physiological signals and inertial signals, it is possible to use ML techniques for the automatic classification of fatigue, with high accuracy. Unfortunately, we believe that there are some critical points that are not analyzed in the literature. In all the articles analyzed, regardless of the accuracy of the fatigue classification, the tasks that the subjects perform are typically very simple, related to repetitive movements and muscle activations. Furthermore, even when more complex tasks are considered, they are too few, and do not generalize an industrial assembly process, where each operator finds himself performing even 20 or 30 different tasks. Some of these tasks are also performed only a few times throughout the assembly line. In addition, the industrial environment presents numerous sources of disturbance, not analyzed in laboratory analysis or in more controlled environments. In this paper, the proposed system tries to tackle the previous shortcomings of the state of the art on fatigue classification. The system is deployed in an actual industrial environment, where it is used to monitor the task performed by 3 operators on a pump assembly line. The system is completely modular and user-friendly in fact, the operators were instructed on how to start and stop the acquisition, with a very intuitive GUI. The system was extensively used to monitor the activities of the operators for 1 month, but this preliminary evaluation will be focused on a reduced dataset, in order to validate the whole system.

## III. PROPOSED IOT SYSTEM FOR MONITORING OPERATORS

To collect data and create a large, reliable dataset suitable for training various ML/DL algorithms to classify fatigue levels, a modular, easy-to-install, and user-friendly IoT system was designed and implemented. The general architecture of the proposed IoT system is shown in Fig. 1.

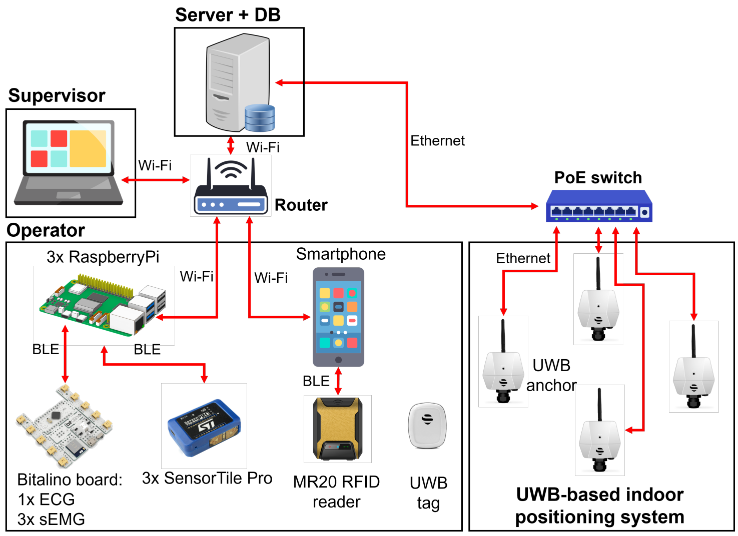


*Fig. 1. General architecture of the proposed IoT-based system*

Each monitored operator wears four types of sensors: (i) a BITalino board [12] for acquiring a precordial ECG signal and three surface EMG (sEMG) signals from the forearm, trapezius, and erector spinae muscles, (ii) three SensorTile Pro inertial measurement units (IMUs) by STMicroelectronics [13] for capturing orientation data, (iii) an MR20 RFID glove reader [14] for identifying passive tags attached to tools and components; and (iv) a UWB tag for indoor positioning measurements. The BITalino board and the IMU on the dominant arm transmit data via Bluetooth Low Energy (BLE) to a Raspberry Pi: the BITalino streams data at 1 kHz per channel, while the IMU streams quaternion data at 100 Hz. In particular, the accuracy of the pitch angle measured by the IMUs has been experimentally evaluated in [15], where uncertainties are lower than 0.2°. Two additional Raspberry Pis are used to collect data at 100 Hz from the non-dominant arm and back IMUs via BLE. This three-device setup was adopted after extensive testing proved it to be the most stable configuration over time. The RFID glove streams the detected tag's EPC value and corresponding RSSI to an Android-based smartphone. All Raspberry Pis are connected to a Wi-Fi router and stream the collected data to a central server with a database. The smartphone application also transmits RFID data to the same server. For indoor positioning, four Sewio UWB anchors [16] are connected to the server via Ethernet through a PoE switch. Each operator wears a UWB tag, and its position is estimated at 10 Hz using Sewio's cloud-based software. On the server, an InfluxDB time-series database is installed. For each operator, a record is maintained with fields corresponding to: (i) ECG and three sEMG signals, (ii) quaternion data from the dominant arm, non-dominant arm, and back, (iii) EPC tag and RSSI from the RFID glove, and (iv) position data from the UWB system. The server also hosts Grafana, an open-source data visualization and monitoring platform. It provides a simple and intuitive interface that allows one or more supervisors to visualize the collected data in real time, with updates every 5 seconds on any laptop connected to the Wi-Fi network. To collect subjective feedback on the perceived fatigue level, each workstation is equipped with five RFID tags numbered from 1 to 5. These tags allow the operator to send the corresponding fatigue level label to the database via the RFID glove reader.

## IV. EXPERIMENTAL CAMPAIGN AND RESULTS

### A. *Experimental campaign*

An extensive experimental campaign was carried out, where the system was installed at EBARA Pumps Europe S.p.A for one month. The system was installed at the pump assembly stations, to monitor the activities of 3 operators during the two daily shifts. The data of the operators who agreed to participate in the experimental campaign were acquired in compliance with privacy regulations, and anonymously, with written consent from the operators. The operators wore the system before starting their work shift. The RFID glove is worn on the right hand, the EMG signals are acquired via electrodes placed on elastic bands, on the back, arm and forearm while the ECG signal is acquired using one of the precordial leads. The BITalino is hooked to the operator's belt. The IMUs were inserted in boxes equipped with an elastic band (like a bracelet) and were placed on both hands, while the one for the back was connected with Velcro strip to a band placed around the chest, and are directly able to acquire quaternions. The UWB tags can instead be worn like a watch. To wear the entire system the operators take 2-3 minutes on average. When the wearing of the system is finished, the operator uses the GUI to start the communication between the sensors, the raspberries and the server. The operator uses the glove to scan a tag placed near the server to signify the beginning of his shift. On each of the stations, RFID tags have been placed on the tools that the operator uses, in addition to 5 tags to express the fatigue. After each task, the operator votes, scanning one of the 5 fatigue tags based on the fatigue vote he wants to assign to that task. The data are sent to the InfluxDB server and then downloaded for processing. The system has been in operation for about a month, but in this paper a preliminary evaluation with a reduced dataset will be included. In particular, the data regarding the assembly of 5 pumps by the 3 operators on the line will be analyzed.

### B. *Features Selection*

In order to classify the fatigue of the operators during the assembly tasks, the signals acquired by the IoT wearable system were processed to obtain features used by the Machine Learning model. Instead of using the raw EMG data, the latter is processed to identify moments of muscle activity. At the beginning, the sEMG signal is band-pass filtered with 4-th order Butterworth filter working at 30 Hz to 300 Hz. To evaluate muscle activity, the Teager–Kaiser Energy Operator (TKEO) is then calculated as follows :

$$TKEO = x(n)^2 - x(n-1) \cdot x(n+1) \tag{1}$$

where, $x(n)$ is the n-th filtered EMG sample. A wavelet decomposition at three levels with a db2 mother wavelet is performed on the TKEO. The signal $\eta(n)$ is calculated from the three coefficients and the residual as follows:

$$\eta(n) = \max_a CWT(a, n) \tag{2}$$

where $a$ is the scale parameter and $CWT(a, n)$ are the estimated coefficients, at each scale factor, and the residual. In this way, $\eta(n)$ contains the highest $CWT(a, n)$ coefficients for each sample, thus increasing the muscle activation detectability. The $\eta(n)$, ECG and quaternions, were divided into 1-second segments, on which the following features were evaluated: Clearance Factor, Crest Factor, Impulse Factor, Kurtosis, Mean, Peak Value, Root Mean Square (RMS), Signal-to-noise Distortion Ratio (SINAD), Signal-to-noise Ratio (SNR), Shape Factor, Skewness, Standard Deviation, Total Harmonic Distortion (THD), Autocorrelation of errors at lag 1 (ACF1), Interquartile Range (IQR), Maximum, Minimum, Median, Quartile 1 and 3 and Maximum Allowable Variation (MAV). Furthermore, on the $\eta(n)$ signal, a threshold is applied to obtain the onset signal (i.e., a signal assuming one value when the threshold is exceeded and zero otherwise), which is also been used as an additional feature for the classifier. The chosen classifier is a bagged ensemble tree with 30 classifiers.

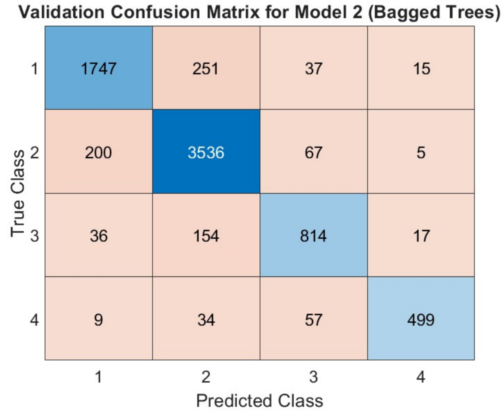


*Fig. 2. Validation Confusion Matrix*

| Fatigue Vote | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| 1 | 92.67 | 87.70 | 85.22 | 86.44 |
| 2 | 90.49 | 88.96 | 92.86 | 90.86 |
| 3 | 95.08 | 83.49 | 79.73 | 81.56 |
| 4 | 98.17 | 93.10 | 83.31 | 87.93 |

*Table 1. Obtained metrics for the Validation Phase*

## V. RESULTS

To train the model, the features of the signals acquired during the assembly of the 5 pumps were divided following an 80-20 split (80 for training and 5-fold validation, and 20 for the test). In particular, the validation/test data split was performed by examining the fatigue scores for each task and then using a Random Number Generator function to mix the data. This was necessary because it ensures that all tasks are present in both training and testing. For the validation of the classifier, the most common metrics used in Machine Learning applications have been calculated for every fatigue vote: Accuracy, Precision, Recall and F1-Score. The validation Confusion Matrix is reported in Figure 2, the validation metrics are reported in Table 1. As can be seen from the confusion matrix and the tables, in the available ground truth, there is no fatigue rating equal to 5. This does not affect the purpose of this work, as these results are related to a first experimental validation. Nevertheless, for the correct generalization of the system, it is necessary to use an expanded dataset, which contains all 5 fatigue declarations. From the analysis of the metrics, it can be noted that the model exhibits an accuracy greater than 90%. From these values, it is therefore possible to declare that this first experimental validation of the model had a positive outcome, and the model is able to effectively classify the fatigue of operators during complex assembly operations, in an industrial environment.

## VI. CONCLUSION AND FUTURE WORK

In this paper, the first experimental results of a wearable IoT system for the classification of fatigue of operators on assembly lines have been presented. The system has been designed to be completely modular, and is composed of (i) aBITalino board for acquiring a precordial ECG signal and three surface EMG (sEMG) signals from the forearm, trapezius, and erector spinae muscles, (ii) three SensorTile Pro inertial measurement units (IMUs) by STMicroelectronics for capturing orientation data, (iii) an MR20 RFID glove reader for identifying passive tags attached to tools and components; and (iv) a UWB tag for indoor positioning measurements. The system was installed and used by operators during the assembly of industrial pumps for one month, and the data from 5 of these assemblies were used for preliminary validation testing of the fatigue classification system. For each task performed, operators assigned a fatigue score, and a set of features in both the time and frequency domains were used to train a bagged ensemble decision tree for classification. From the results obtained it is possible to verify that the system correctly classifies the fatigue of the operators on the different tasks with accuracies greater than 90%. Future works will be focused on expanding the dataset, using the full month-long available dataset for the training of the model, to improve generalization and to evaluate the performance of the classification on more data, and to implement the classification system to be able to work in real-time, while the operators perform the assembly operations.


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