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Machine Learning approach towards real time assessment of hand-arm vibration risk

G. Aiello *, A. Certa**, Islam Abusohyon***, Francesco Longo**** Antonio Padovano****

** Department of Engineering, University of Palermo, 90128, Palermo, Italy (giuseppe.aiello03@unipa.it).*
*** Department of Engineering, University of Palermo, 90128, Palermo, Italy (antonella.certa@unipa.it).*
**** Department of Mechanical, Energy, Management and Transportation Engineering, University of Genova, , 16145 Genova, Italy - (easem288@gmail.com)*
***** Department of Mechanical, Energy and Management Engineering, University of Calabria, 87036 Rende, Italy; f.longo@unical.it).*
****** Department of Mechanical, Energy and Management Engineering, University of Calabria, 87036 Rende, Italy; antonio.padovano@unical.it).*

Abstract: In industry 4,0, the establishment of an interconnected environment where human operators cooperate with the machines offers the opportunity for substantially improving the ergonomics and safety conditions of the workplace. This topic is discussed in the paper referring to the vibration risk, which is a well-known cause of work-related pathologies. A wearable device has been developed to collect vibration data and to segment the signals obtained in time windows. A machine learning classifier is then proposed to recognize the worker's activity and to evaluate the exposure to vibration risks. The experimental results demonstrate the feasibility and effectiveness of the methodology proposed.

Keywords: Accelerometers, Artificial intelligence, activity recognition, vibration risk

1. INTRODUCTION

The smart factory concept promoted by industry 4.0, is expected to drastically change the interaction among human operators and machines, with advanced human-machine interfaces (HMI), augmented reality, and wearable devices becoming part of the standard worker's equipment. Coherently with such view, the manufacturers of operating machines are implementing artificial intelligence features in their products, transforming automated machines into cyber physical systems (CPS), with advanced interoperability functions, ideally allowing them to interact with the other systems, with the environment and with the human operators in seamless integrated production site. In such regard, the establishment of the smart factory paradigm has enriched the scope of ergonomics with new technological and methodological elements, fostering the development of a systematic and integrated approach towards the design of future manufacturing environments. According to such view, the topic of the "Smart Operator" or "operator 4.0" has been recently introduced (Longo *et al.* 2017, Kong *et al.* 2018) as the counterpart of the smart factory concept, with the objective of aligning and enhancing operators' capabilities/competencies with the new smart production environment. The issues related to next generation human-machine interaction and worker's wellbeing should also be discussed in consideration of the ageing process that is affecting the workforce of many industrialized countries, whose impact on manufacturing systems' performances has been highlighted by a recent study by Calzavara *et al.* (2020).The European population, in particular, is projected to grow from 507.2 million in 2013 to 522.8 million in 2060, with the percentage of seniors (65 years or older) forecasted to grow by 10%, while the working age population is expected to drop by 9.4% (EC 2017). In a manufacturing environment, human operators' capabilities of performing a task, requiring physical and/or cognitive efforts generally diminish with ageing (Gonzalez and Morer 2016; Strasser 2018), however, the impact that this decrease can have on the system's productivity can be minimized if the workplace is healthy and safe. Rethinking the role of the human operator in a general ergonomic framework is thus a major challenge to undertake within the 4th industrial revolution, in a renewed approach involving new technologies and methodologies. In the current industrial practice, indeed, ergonomics is still frequently approached with standard worksheets filled by experts and processed with statistical tools rather than on real time quantitative measurements. In such regard, the enabling technologies of industry 4.0 offer an unprecedented occasion for improving the health and safety conditions of the workplace through real-time data gathering and analytics.

This paper aims at contributing to the existing research in the context of operators' ergonomics and safety in smart production environments, by demonstrating the technical feasibility and the effectiveness of the current technologies in monitoring the workers' conditions in real time and by proposing a novel approach to occupational health and safety in the smart industry context through the digitalization of risk-related data. The research involves a Human Activity Recognition (HAR) methodology to recognize the activities performed by each operator during the work shift, and to map the corresponding exposure towards health risks. Human Activity Recognition (HAR) is a consolidated research topic

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focused on the automatic detection and recognition of the activities of a person or a group of people through the analysis of relevant data related to their operations. The roots of HAR system can be traced in the activity theory, originally developed by the Russian psychologist Leontev (1978) back in the 80's, which defines the fundamental theoretical reference framework for classifying human activities. The activity theory introduces a hierarchical structure where activities are described as an aggregation of actions, which, in turn, are understood as a set of atomic steps named operations. Such approaches ultimately aimed at simulating the human ability of extracting significant elements from redundant or confused information, thus falling in the broader framework of machine learning (ML) methods. ML is a research field initiated in 1959 with the objective of developing computer systems with the ability to learn without being explicitly programmed (Samuel, 1959). The first practical applications of pattern recognition systems were mainly based on the stochastic discrimination of characteristic patterns in noisy datasets such as texts, images or sounds. The integration with on-body sensing technologies however started approximately 20 years later. Nowadays, after more than 50 years of research, ML has become an important interdisciplinary research area, while the proliferation of electronic sensing devices, promoted the spread of sensor based HAR systems in several fields including industry, medicine, assisted living, etc. Recently, applications of HAR technology have also been proposed in the context of ergonomics and safety (Nath et al., 2018), where several typologies of body-mounted sensors have been employed within automatic ergonomic assessment methods based on the classification of the activities performed by workers. In particular, a consistent body of scientific literature focuses on vibration-based activity recognition methods, exploiting the data gathered by accelerometers integrated into the workers' equipment. The first relevant results in the classification of human activities based on accelerometer data appeared at the beginning of the new millennium when Bao & Intille (2004) and Ravi et al (2005) formulated the activity recognition problem as a modern classification problem. The first industrial experimentations appeared some years later when Joshua and Varghese (2011) explored the application of accelerometer in construction industry for work sampling, while Ahn *et al.* (2013) used a set of features calculated from acceleration data to classify excavator operations into three classes. The limited computational capabilities and the high cost of the data gathering devices at that time substantially hampered the spread of such methodology, which therefore remained confined to the domain of research. A major paradigm shift occurred in the last decade due to the popularization of smartphones featuring powerful miniaturized accelerometers based on Micro-Electro-Mechanical Systems (MEMS). Several smartphone applications of vibration based HAR systems have thus appeared in the last years, with significant contributions also in the industrial context where vibration analysis has been employed for monitoring and classifying the activities of construction workers (see e.g. Akhavian and Behzadan 2016, Zhang *et al*., 2018). From a methodological point of view, the approaches reported in the literature generally refer to the classification of activities based on the recognition of specific patterns in the features extracted from vibration signals. Such approaches mostly rely on heuristic handcrafted features, including significant statistics extracted from the raw signal in the time or in the frequency domain. Classification methods, such as decision trees, k-Nearest Neighbor, and Support Vector Machines, are then trained to identify different activities. This research focuses on the health risks related to vibrations, which, affect an average of 19% workers in Europe, with Agriculture, Manufacturing and Construction being the most critical sectors Eurofound's (2015). The vibrations originating from tools or machinery can cause occupational diseases such as the hand-arm vibration syndrome (HAVS). Therefore, institutions have issued specific regulations to enforce surveillance actions and prevention measures, and to assign specific responsibilities to the manufacturers of the power tools, to the employers and also, partly, to the workers themselves. In particular, the EU Directive 2002/44/EC defines an "action value" as a threshold for triggering corrective actions, and "exposure limit" which, once reached, forces the worker to stop his activity. Such values are established equal to 2.5ms^{-2} and 5ms^{-2} respectively. The average daily vibration is calculated according to the EN ISO 5349-1:200, based on reference vibration levels generally provided by the tool manufacturers. This approach is however questionable as in fact the effective vibration intensity generated by mechanical machines largely depends upon several specific factors including, maintenance, operating conditions, etc. It is not unusual, hence, that the same tools generate substantially different vibrations when performing different tasks. A precise measurement of the actual vibration exposure originating from specific tasks in industry context should rather be employed to obtain more realistic values. To overcome the above discussed issues this research proposes a novel system and related methodology for mapping the different tasks performed by an operator during its work shift, and the associated vibration dose, thus providing information about operators' risk exposure.

2. METHODOLOGY

The methodological approach aims at mapping the activities performed by a set of operators in the manufacturing industry and at associating their corresponding risk exposure in order to obtain an overall representation of the safety conditions in a smart factory. The methodology established is based on ML procedures exploiting the could interconnection functionalities and IoT technologies promoted by industry 4.0, can be subdivided into two main steps: the analysis of the acceleration data streams gathered by a wearable sensing device, and the assessment of the corresponding hand-harm vibration risk exposure. Such phases are discussed below.

2.1 Recognition and Classification of worker's activity.

The methodology proposed for classifying the activities performed by the workers is based on the analysis of the vibration signals acquired by two accelerometers integrated in a wearable device through the implementation of a typical Activity Recognition Chain (ARC) (Bulling *et al.*, 2014), involving the following steps: data collection, pre-processing, segmentation, feature extraction, and classification. According to this approach, the input vibration data collected by a sensing device are validated, and subdivided into segments of fixed, length named windows. The relevant features are then extracted from each window and fed into a machine learning classifier to categorize them into a set of pre-established classes. In the case here proposed the classes are referred to the different basic operations performed by means of rotating tools into a smart factory (e.g. grinding, polishing, cutting, etc.) within a general task assigned to the operator. The methodology has been finally validated in the laboratory by performing a set of experiments, and the accuracy of the classification has been evaluated.

Data collection has been carried out by means of a smart wearable prototype device specifically designed and developed for the purpose of this research. The system features two high performance tri-axial accelerometers fixed to the wrists of the operator and cable-connected to the main sensing device, attached to his waist. The instant tri-axial raw acceleration data are recorded for each hand, while the worker is performing his regular activities (related to the assigned tasks), thus obtaining two distinct data streams, each one consisting of the timestamped X, Y, Z accelerations values. The volume of the data generated, and the consequent computational effort required for processing them, is strictly related to the polling frequency, which must be accurately established considering the technical limitations of the hardware employed. Subsequently, the data pre-processing step involves an evaluation of the consistency of the data read by the sensors, which could be affected by artifacts deriving from e.g. out-of-range readings, electro-magnetic noise and interferences in the data transfer, or from hardware failures. Corrupted data due to partial readings are filled with the last valid reading, thus obtaining regular triplets stored into time-stamped vectors as valid inputs for the subsequent processing steps.

The Segmentation step involves the subdivision of the vibration data streams into windows of fixed length, and is performed before the feature extraction procedure, in order to reduce the dimensions of the datasets. Data segmentation also reduces the computational effort required for extracting the relevant features in big datasets, which may otherwise result in significant delays, particularly when embedded systems with limited hardware capabilities are employed for real time applications, as in the case here considered. The establishment of an appropriate segmentation process depends upon the specific application considered, being generally recognized that longer time windows improve the accuracy of the recognition process, but result in increased computational effort for feature extraction. Establishing an appropriate length for data segmentation is thus a substantial issue, and advanced techniques involving variable length and overlapping windows have been proposed in the literature to improve the results Referring to the analysis of vibration levels, however, Preece *et al.* (2009) observed that existing studies reported in the literature, generally do not consider time segments rarely exceeding 10s, with polling frequencies mostly varying from 20Hz to 100Hz. Considering the advances in the computational capabilities of the CPUs designed for smart devices, in the last decade, however, it is nowadays possible to process significantly bigger amounts of data in small time, and the windows length and polling frequency can thus be substantially increased. The sensing device employed in this study can generate two separate data streams (one for e ach accelerometer) at up to 1600 readings per second, with each measure consisting of three acceleration values in X, Y and Z axes. In such conditions, a time frame of 1 minute can contain as much as 384 000 time-stamped values per stream. In the application considered in this study, the device was able to seamless process data segments of 40 secs in quasi real time in the experimental tests.

Feature extraction is essentially a dimensionality reduction process, based on the transformation of each raw-data segment into a restricted feature-space through appropriate numerical methods and computational approaches. Clearly, the choice of an appropriate set of meaningful features is of critical importance in this phase, in order to preserve the inherent knowledge for an accurate classification process. Contrarily, unnecessary features or redundant information would only affect the performance of the classification algorithms without scientifically improving the final result. In the case of data collected from inertial sensors, the features commonly extracted can be classified into time domain and frequency domain features. In this study, seven popular time domain features have been extracted for each axis in each window (table 1).

Table 1. Time domain features for activity recognition

Feature name	Formula
Mean	$\bar{x} = \sum_{x_i \in W} x_i / N$
Standard deviation	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}}$
Maximum	$Min = \min_{x_i \in W}\{x_i\}$
Minimum	$Max = \max_{x_i \in W}\{x_i\}$
Root Mean Square	$RMS = \sqrt{\frac{1}{\mathrm{N}} \sum_{x_i \in W} x_i^2}$
skewness	$S = \frac{1}{N}\left[\frac{\sum_{i=1}^{N}(x_i - \bar{x})}{\sigma}\right]^3$
Kurtosis	$K = \frac{1}{N}\left[\frac{\sum_{i=1}^{N}(x_i - \bar{x})}{\sigma}\right]^4$

The classification process is the last step of the activity recognition chain and consists in discriminating the feature space representation of the segments into one (binary classification) or more (multiclass classification) categories. In the context of ML, the classification process is implemented through the development mathematical functions and algorithms named classifiers. When the classification process relies on an initial knowledge provided as a reference set of pre-classified instances, the corresponding classifier is an instance of supervised learning methods. Recognizing the different possible activities performed by a tool operator in a manufacturing industry, properly configures as a multiclass classification process. However, in this paper to simplify the classification process, the activities have been regrouped into heavy-duty (HD) and low-duty (LD) as reported in table 2.

Table 2. Activity Classification in heavy duty (HD) and low duty (LD)

Operation	Tool type	Type	Vibration level (ahw)
Surface finishing	Palm grip orbital sander	LD	5-10
Rough solder grinding	Right angle sander	HD	15-25
Metal trimming	Trimming shear	HD	20-30
Paint repair	Jitterbug sander	LD	4-8
Paint polishing	Polisher	LD	4-8
Rust removing	Stone grinder	HD	20-30
Metal cutting	rotating carbon blade cutter	HD	25-40

Based on the above considerations, in this paper a binary classifier has been developed in order to discriminate between HD and LD activities referring to their vibration signatures. The classification problem has thus been approached by means of the well-known K-Nearest Neighbor (KNN) classifier, which assigns each new instance to a specific class according to its distance from the k most similar instances already classified. Despite its simplicity, the KNN algorithm has revealed a robust and versatile classifier, combining a good accuracy with a limited computational effort, and outperforming more complex classifiers in many real-time applications. In such regard, a crucial role on the accuracy of the classification is played by the establishment of a suitable distance metric and by the number of neighbors (k) considered. The influence of such parameters on the performance of the algorithm is still a widely discussed topic, however, the Euclidean distance is the most used metric, and more rarely different metrics such as Manhattan or Hamming distance are employed. The k parameter influences the shape of the decision boundary, with small values resulting in a higher influence of noise on the classification, and large values substantially increasing the computational effort. Given the lack of appropriate optimization approaches, its value is generally established empirically by a trial and an error.

2.2 Risk evaluation

The second element of the methodology proposed concerns the real-time quantitative evaluation of the hand-arm risk exposure associated to the operations performed. The procedure established for such purpose is performed after the segmentation step and consists in analyzing the vibration data in each segment according to the guidelines provided in ISO 5349-1 (2001a) and ISO 5349-2 (2001b). According to such guidelines, the vibration dose transmitted to the operator's hands is related to the root-mean square (rms) frequency-weighted acceleration value. The vibration spectrum must thus be extracted from the raw acceleration data by means of Fast Fourier Transformation (FFT) and analysed in 1/3 octave bands. Subsequently, the root mean squared (rms) intensity in each band must be calculated and multiplied by an appropriate weighting factor representing the corresponding physiological effect. The frequency weighted acceleration can thus be calculated as:

$$a_{hw(x,y,z)} = \left[\sum_{j=1}^{n}\left(W_j \cdot a_{w,j(x,y,z)}\right)^2\right]^{\frac{1}{2}} \tag{1}$$

where $a_{w,j}$ is the acceleration measured in the one-third octave band in m/s^2, and W_j is the weighting factor of the corresponding one-third-octave band. The evaluation of vibration exposure in accordance with ISO 5349 is finally obtained as the root-sum-of-squares (vibration total value) of the three component values:

$$a_{hw} = \sqrt{a_{hw(x)}^2 + a_{hw(y)}^2 + a_{hw(z)}^2} \tag{2}$$

where $a_{hw(x)}$, $a_{hw(y)}$, $a_{hw(z)}$ are the frequency-weighted acceleration values for the single axes.

The vibration exposure finally depends upon the magnitude of the total vibration value and the daily exposure expressed in terms of the 8-hour energy-equivalent acceleration:

$$A(8) = a_{hw}\sqrt{\frac{T}{T_0}} \tag{3}$$

where T is the total daily duration of the exposure (s), and T_0 is the reference duration of 8 h.

The energy-equivalent acceleration is obtained considering the daily exposure time required to produce adverse health effects is inversely proportional to the square of frequency-weighted acceleration. To ease the development of real time risk evaluation tools, an effective approach is to consider an equivalent vibration score (VS) factor, calculated according to eq. 4.

$$VS = a_{hw} \cdot T^2 \tag{4}$$

The employment of the vibration score rather than 8-hour energy equivalent acceleration has proven to be an effective approach in real-time risk assessment (Catania et al. 2019), since it allows to update the worker's risk exposure level at each new data segment acquired. Finally, decision related to the worker's safety can be undertaken by comparing the instantaneous vibration score with the action threshold and maximum allowable dose, coherently calculated (eq. 5 a,b)

$$VS^{action} = 8 \cdot 5^2 = 200 \tag{5a}$$

$$VS^{maximum} = 8 \cdot 2{,}5^2 = 50 \tag{5b}$$

3. RESULTS AND DISCUSSION

To demonstrate the effectiveness of the approach proposed, an experimental analysis has been performed through a set of lab experiments where the operations given in tab 2, have been simulated using real tools typically employed in the manufacturing industry. The vibration signals generated during the lab tests have been gathered by means of a device protype specifically developed for the purpose of this research. The data gathering device is the evolution of a previous system (aiello et al., 2012) and features two cable-connected triaxial accelerometers fixed to the wrists of the operator, and is based on the Raspberry PI4 "system-on-chip" platform, featuring a 1.5 GHz 64-bit quad core ARM Cortex-A72 processor, 4GB RAM, WLAN and full gigabit ethernet, integrated in a single board. The raspberry system has been connected with via I2C to two high-performance Bosch Sensortec BMI270 smart inertial measurement units (IMU) with a measurement range of ±16g and a maximum Output data Rate (ODR) of 1.6 kHz. The device if finally connected to the WiFi network, which enables the communication with a centralized system capable of gathering and analyzing the data transmitted by several devices. The system is finally equipped with a 20 000 mAh Li-po rechargeable battery for DC power supply, allowing for several hours of autonomous operations, thanks to the high energy-efficiency of the BMI270 MEMS sensors and the low power consumption of the raspberry board. The Vibration signals acquired during several lab tests have been segmented into windows of 40 seconds containing 64000 values and stored in the local memory. The pre-processing and feature extraction activities are performed locally on the wearable device, as well as risk assessment calculations. The system is thus structured according to a decentralized architecture, with the wearable devices performing most of the data processing functions on data streams of 99 segments per hour per hand. Such decentralized solution, is highly scalable and previous studies (Aiello *et al.*, 2017) have demonstrated its effectiveness in monitoring the risk exposure of several workers simultaneously.

The data streams have been further subdivided into segments of 40 secs, obtaining a database of more than 2000 segments. The data thus obtained have been subsequently fed into the k-nn classifier in order to evaluate its performance in categorizing the data into HD and LD classes. For such purpose, a cross validation process has been performed, where the original dataset has been randomly partitioned into k subsets P_1, P_2, …, P_k of equal size. Each partition is then subdivided into a validation set and a training set and processed by the classifier. The accuracy of the classification has then been estimated evaluating the proportion of instances correctly predicted by the classifier. The accuracies obtained for each partition have been finally averaged to obtain an overall score. In particular, in the case here presented, the overall dataset has been pre-classified into HD and LD operations, subsequently 20 Partitions of 500 segments each were obtained extracting random segments from the entire dataset, and each partition was subdivided into a training set and a validation set of 100 and 400 instances respectively. The accuracy of the classification obtained has finally been evaluated according to eq. 6.

$$Accuracy = \frac{\#correct\ classifications}{\#\ dataset\ dimension} = \frac{TP+TN}{TP+FP+TN+FN} \quad (6)$$

Where TP (true positive) is the number of samples correctly attributed to the HD class and TN (true negative) is the number of instances correctly attributed to the LD class. FP (False Positives), and FN (false negatives) are referred to misclassified instances.

The classification results were thus obtained considering different values of k. The results show that increasing the value of k from 3 to 7, the average number of errors (FN+FP) increases from 7,55 to 35,60 (over 100 instances classified) while the overall accuracy decreases from 92% to 74%. Based on these results it can be concluded that the k=3 classifier performed best, and such good performance is mainly due to the good results obtained in classifying HD instances.

Table 3. Accuracy of Classification

Operation	Accuracy
K = 3	0,94
K = 5	0,80
K = 7	0,74

Finally, the vibration risk associated with the activities has been evaluated by performing a FFT transform of the vibration signals in each segment, and calculating the weighted average vibration factor, considering the ISO weighting curve. Subsequently, the vibration score (VS) has been calculated according to eq. 4, and the overall map of the single operations performed and corresponding worker's exposure to vibration risk during the execution of a complex task has thus been constructed. Such result is depicted in the following fig. 1 referred to a task involving 7 elementary operations performed in approx. 180 mins.

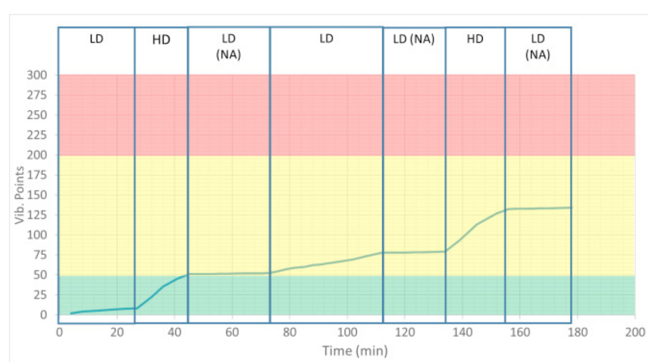

Fig. 1. worker's vibration risk related to a task. LD=Low Duty, HD=High Duty, NA=No Activity

The feature extracted from each segment were then fed into the k-nn classifier. The results obtained show all the operations were classified into HD and LD classes, thus allowing to map the complete task and to associate the corresponding overall risk exposure.

4. CONCLUSIONS

While the smart factory concept spreads in the manufacturing industry, operators are still frequently performing their activities in uncomfortable, stressful or dangerous environments and the industrial approaches towards ergonomics and safety frequently often appear outdated and inadequate. Providing enterprises with new and more effective methods to enhance the health and safety condition of the work environment becomes mandatory to ensure adequate wellbeing conditions in the workplace and to prevent the occurrence of work-related pathologies. This research proposes a new methodology for the surveillance of workers' wellbeing conditions and for preventing musco-skeletal pathologies related to hand-harm vibrations. The approach developed is based on state-of-the-art sensing technologies and machine-learning methods for automatically mapping the activities performed by the operators, and evaluating the actual vibration dose received. In particular, the study proposes a k-nn classifier for recognizing the workers' activities through the features extracted from vibration signals, and a real time vibration risk assessment methodology for associating their corresponding risk exposure. In addition, a wearable device has been developed, capable of transmitting relevant information about the workers' wellbeing and safety conditions taking advantage of IoT technologies in an interconnected work environment. The system and the methodology have been validated in the lab by simulating some operations frequently performed by operators in several industrial contexts. The results obtained demonstrate the effectiveness of the methodology proposed with an overall accuracy of the classifier above 90%. With such performance level, not only the system can be an effective tool to increase the workers' awareness about the safety condition of the workplace, but it can also support the surveillance activity of the managers, suggesting appropriate preventive and corrective actions.

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