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Worker safety in agriculture 4.0: a new approach for mapping operator's vibration risk through Machine Learning activity recognition

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Abstract:	While being a fundamental driver of competitiveness in agroindustry, technological innovation has also introduced new critical elements related, for example, to the sustainability of the production processes as well as to the safety of workers. In such regard, the advent of the 4 th industrial revolution (Agriculture 4.0) based on digitalization, is an unprecedented opportunity of rethinking the role of innovation in a new human-centric perspective. In particular, the establishment of an interconnected work environment and the augmentation of the operator's physical, sensorial, and cognitive capabilities, are two technologies which can be effectively employed for substantially improving the ergonomics and safety conditions on the workplace. This paper approaches such topic referring to the vibration risk, which is a well-known cause of work-related pathologies, and proposes an original methodology for mapping the risk exposure of the operators to the activities performed. A miniaturized wearable device is employed to collect vibration data, and the signals obtained are segmented in time windows and processed in order to extract the significant features. Finally, a machine learning classifier has been developed to recognize the worker's activity and to evaluate the related exposure to vibration risks. To validate the methodology proposed, an experimental analysis in real operating conditions has been finally carried out by monitoring the activities performed by a team of workers during harvesting operations. The results obtained demonstrate the feasibility and the effectiveness of the methodology proposed.
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To Editorial Department of

Computers and Electronics in Agriculture

Object: Cover Letter for the manuscript "Worker safety in agriculture 4.0: a new approach for mapping operator's vibration risk through Machine Learning activity recognition".

Dear Editor,

I am submitting the manuscript entitled "Worker safety in agriculture 4.0: a new approach for mapping operator's vibration risk through Machine Learning activity recognition", for consideration of publication in Computers and Electronics in Agriculture. The manuscript discusses the application of machine learning methods for activity recognition and risk assessment in agriculture, and reports the results of experimental tests in olive harvesting.

The manuscript has not been published nor has it been ever submitted elsewhere.

Thank you for your consideration.

Giuseppe Aiello

Highlights

- Recognize operator’s activities through a machine learning classifier
- Assess Vibration risk in real time to enhance operator’s safety
- Develop a lightweight wearable device for real time monitoring
- Validate the process in real conditions through experimental tests

Worker safety in agriculture 4.0: a new approach for mapping operator's vibration risk through Machine Learning activity recognition

Abstract

While being a fundamental driver of competitiveness in agroindustry, technological innovation has also introduced new critical elements related, for example, to the sustainability of the production processes as well as to the safety of workers. In such regard, the advent of the 4th industrial revolution (Agriculture 4.0) based on digitalization, is an unprecedented opportunity of rethinking the role of innovation in a new human-centric perspective. In particular, the establishment of an interconnected work environment and the augmentation of the operator's physical, sensorial, and cognitive capabilities, are two technologies which can be effectively employed for substantially improving the ergonomics and safety conditions on the workplace. This paper approaches such topic referring to the vibration risk, which is a well-known cause of work-related pathologies, and proposes an original methodology for mapping the risk exposure of the operators to the activities performed. A miniaturized wearable device is employed to collect vibration data, and the signals obtained are segmented in time windows and processed in order to extract the significant features. Finally, a machine learning classifier has been developed to recognize the worker's activity and to evaluate the related exposure to vibration risks. To validate the methodology proposed, an experimental analysis in real operating conditions has been finally carried out by monitoring the activities performed by a team of workers during harvesting operations. The results obtained demonstrate the feasibility and the effectiveness of the methodology proposed.

Keywords: Operator safety, vibration risk, machine learning, real time monitoring

1. Introduction

In the last decade, the so-called 4th industrial revolution, or industry 4.0 has promoted a substantial renewal of industrial processes, based on the interconnection of the production resources and on the valorization of digital information. Promoted by significant investments from public institutions and private companies, this renewal process has grown to a global scale, originating new business models based on digital information to support and strengthen the value chain of enterprises (Strange and Zucchella, 2017). The disruptive potential of such revolution has spread beyond the boundaries of industrial manufacturing, encompassing and influencing all industry fields related to the provision of products and services. The agroindustry sector has embraced the digital revolution, recognizing the unprecedented opportunity it offers to provide a reliable response to the demands of our future society in terms of demographics, scarcity of natural resources, climate change, and food waste.

Differently from past innovations, mainly centered on the intensive exploitation of resources to increase yields and production rates, Agriculture 4.0 or Smart Farming (Lezoche et al., 2020, De Clercq et al. 2018, Rose and Chilvers, 2018) substantially relies on the employment of digital technologies for strengthening the value chain of agro-industrial enterprises. The next generation agroindustry systems, will hence exploit digitalization technologies, such as the Internet of Things, Cloud Computing, robotics, and Artificial Intelligence (AI) to redesign the value-creation processes through a substantial innovation in the interaction among the operators and the machines (Benos et al., 2020). In such regard, Agriculture 4.0 will also represent an epochal shift towards a human-centric view of the production environment, where the role of the operator will be reconsidered in a renewed approach towards ergonomics and safety, envisioning new technologies and methodologies aimed at preventing work-related health diseases. In the current agroindustry practice, indeed, ergonomics and safety are still frequently approached with standard worksheets filled by experts and processed with statistical tools, and rarely involving real time quantitative measurements. Considering the possibilities offered by the modern technologies, these approaches appear obsolete and somewhat inadequate, in the general context of the smart production environment, particularly when high-demanding operations are involved, as frequently in agroindustry. The opportunities offered by new technologies in developing next generation human-machine interfaces are also of paramount importance in consideration of the ageing process that is affecting the agricultural workforce of many industrialized countries. 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). The impact the ageing process on operator’s performance is currently a substantial concern for industrial and agricultural organization, as discussed for example by Calzavara et al. (2020) and Reed and Claunch (2015). In such regard, the recent advances in sensing technologies offer a substantial occasion for improving the health and safety conditions of the workplace. Such technologies are nowadays becoming popular and cheap devices can be easily found on the market (e.g. for fitness or medical purposes), although their employment in agro-industry context is still limited. Clearly, the development of such devices for safety purposes, not only involves a suitable hardware configuration, but it also requires the establishment of appropriate methodologies for measuring the workers’ exposure to physical (e.g. vibrations) and cognitive (e.g. fatigue) hazards, their wellbeing status (e.g. the presence of stress markers in biological fluids), as well as the health and safety conditions of the workplace (e.g. wrong postures or the presence of dangerous substances).

This research, in particular, focuses on the health risks related to vibrations, which, according to Eurofound’s (2016) sixth European working conditions survey (EWCS), affect an average of 20% workers in Europe (proportion of workers in EU28 exposed one-quarter of the time or more to vibration risks from hand tools and machinery in 2015) with Agriculture, Manufacturing and Construction being the most critical sectors. In such contexts, the vibrations originating from tools or machineries can cause occupational diseases such as the hand-arm vibration syndrome (HAVS). Therefore, national and international institutions have issued appropriate regulations to enforce surveillance actions and prevention measures, and to assign specific responsibilities to the manufacturers, to the employers and also, partly, to the workers themselves. In particular, the machinery directive (2006/42/EC) requires the manufacturers to implement in their tools and equipment appropriate technical solutions aimed at reducing the vibration levels. The employers are in charge for monitoring risks in order to preserve the health of the operators, while the workers are responsible for using the tools according to the given instructions and to report the occurrence of unusually high vibration levels during their activity. Such prescriptions nowadays are applied only to a limited extent, not necessarily due to the negligence of the subjects involved, but rather because of the technical difficulties in measuring and assessing the risk exposure for workers, considering the lack of suitable real-time measurement instruments (Podgorski et al 2017, Bernal et al 2017). Consequently, the subjects involved are scarcely aware about the actual risk exposure of workers, and corrective actions are seldom triggered timely. It is hence necessary to provide organizations with adequate tools and systems capable of increasing their awareness about vibration hazards, thus introducing work breaks when necessary, restricting the operating time during the workday, scheduling the tasks in order to alternate the use of vibrating and non-vibrating tools and triggering safety measures when necessary.

The exposure to vibration risk is a main concern in agriculture, since vibrating tools such as tractors, shakers, harvesters, etc. are commonly employed in several operations. Mechanized fruit harvesting, for example, is a common practice in modern agri-food chains, due the substantial cost reduction it allows compared to manual harvesting. For example, the employment of hand-held harvesters or shakers equipped with electric or combustion engines in olive harvesting has been demonstrated to increase the field working capacity by even two to three times (Carrara et al., 2007) with a yield of 90-95%, (Sola-Guirado et al., 2014; Castillo-Ruiz et al., 2015; Bernardi et al., 2016). Portable harvesters however are a well-known cause health risks related to vibrations (Pascuzzi et al., 2009; Aiello et al, 2012), therefore their employment must be accurately scheduled, to avoid an excessive risks exposure of the workers involved. In such situations, the team of operators should hence be appropriately managed to maximize the efficiency of harvesting while complying with the prescriptions of safety regulations for limiting the exposure to vibration risks. The vibration dose that each operator daily accumulates during his operations, can thus be regarded as a safety “budget”, that must be accurately allocated to achieve an optimum compromise between efficiency and safety (Aiello et al. 2019). A precise map of the operators’ risk exposure with respect to the operations performed could be a substantial information for the workers who could be aware of their level of risk exposure, but it could also substantially support the management in improving the schedules in order to prevent health risks for the workers.

Based on such premises, this paper aims at contributing to the existing literature in the context of ergonomics and safety in agroindustry, by targeting the following research objectives:

- evaluating the effectiveness of state-of-the-art machine learning methods for activity recognition in agroindustry and risk assessment;
- demonstrating the technical feasibility and the effectiveness of the current technologies in monitoring the workers’ exposure to vibration risks in real time.
- proposing a novel approach to occupational health and safety in agroindustry based on the digitalization of risk-related data.

In the reminder of the paper, after introducing the relevant scientific literature in section 2, a methodology based on the employment of digital sensor data and Machine Learning methods will be presented. In the 4th paragraph the effectiveness of the proposed approach is discussed based on experimental results obtained through in laboratory experiments. The conclusions then discussed in section 5, where also the managerial insights are highlighted.

2. Literature review

The studies about the interaction between the human operators and the machines can be traced back to the last century, when, the introduction of mechanization in agriculture brought a significant improvement in the cost-effectiveness of the production processes. The research, at that time, was mainly focused on the optimization of the performance of the machines, while the workers had to adapt to the systems' processes. The shift towards a human-centric view of the work environment, emerged only at the end of the last century, when the principles of occupational health and safety were placed at the core of the ergonomics science, in a modern approach towards human-machine interaction. Industrial ergonomics is recognized nowadays as an important and scientifically consistent research topic, attracting a multidisciplinary research effort. Referring to the agro-industrial sector, the recent establishment of the Agriculture 4.0 paradigm (Lezoche et al., 2020, De Clercq et al. 2018, Rose and Chilvers, 2018), has enriched the scope of ergonomics with new technological and methodological elements, fostering the development of safer and healthier production operations. According to such view, the concept of the "Smart Operator" or "operator 4.0", recently introduced (Longo et al 2020, Ruppert et al 2018, Romero et al 2017, Kong et al 2018) in the manufacturing industry with the objective of aligning and enhancing operators' capabilities/competencies with the new production environment, can be straightforwardly extended to the agroindustry sector. This evolution of the operator's role is supported by the methodological and technological advances promoted by the fourth industrial revolution, including wireless interconnection technologies (IoT), Big Data Analysis, and Artificial Intelligence, etc. The application of such technologies in conjunction with Human Activity Recognition (HAR) methodologies can open a wide landscape of new applications related to the analysis and classification of the operators' activities. HAR is a consolidated research topic focused on the automatic detection and recognition of the activities of a person or a group of persons 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) 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 set of atomic steps named operations. The early efforts in the development of activity recognition systems begun with the formulation of suitable methodologies to recollect the structure of operators' activities from the analysis of data related to the operations performed, fused with additional context information. 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*)*. Driven by the increase in computational capabilities offered by electronic calculators, the first practical applications of pattern recognition systems were mainly based on the stochastic discrimination of characteristic patterns in noisy datasets (Devijver and Kittler, 1982) such as texts, images or sounds. The integration with on-body sensing technologies started approximately 20 years later, with the studies of Randell and Muller (2000). Nowadays, after more than 50 years of research, ML has become an important interdisciplinary research area, involving sensor based and video based recognition systems. The original toolset of statistical methodologies has also enriched with more complex and computationally demanding techniques allowing for real-time analysis of complex patterns in big amounts of data. Modern ML methods can thus be distinguished into two broad classes, namely supervised learning, involving human expert's knowledge in a preliminary stage, and unsupervised learning where the reconstruction of an inherent structure of the data is entirely entrusted to the machine. The class of supervised machine learning methods typically includes regression (e.g. generalized linear models, support vector regression, decision trees, ensemble methods, trained neural networks) and classification techniques (e.g. support vector machines, k-nearest neighbor, discriminant analysis), while clustering (e.g. hierarchical, k-means, Hidden Markov Models) and association techniques belong to the class of unsupervised machine learning.

The proliferation of electronic sensing devices, in the last decade, promoted the spread of sensor based HAR systems in several fields including industry (Akhavian and Behzadan 2018), medicine (Patel et al 2012, Schrader et al., 2020), assisted living (Ghasemi and Pouyan,2016), etc. Recently, applications of HAR technology have also been proposed in the context of ergonomics and safety (Nath et al., 2018, Malaisè et al., 2019), 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 such regard 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. 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, 2017).

While the technologies for activity monitoring are spreading in a pervasive manner, 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. In particular, such approaches mostly rely on heuristic handcrafted features, also known as shallow features, including significant statistics extracted from the raw signal (e.g., std, avg, mean, max, min, median, etc.) in the time domain (Bao, & Intille, 2004; Heinz, et al. 2003; Kern et al., 2003), or in the frequency domain (Krause et al., 2003, Nham et al., 2008). Classification methods, such as decision trees (Bao et al 2004, Mannini & Sabatini 2010), k-Nearest Neighbor (Ravi et al. 2005), and Support Vector Machines (Anguita et al, 2012), are then trained to identify different activities. An extensive survey on wearable sensor-based HAR can be found in (Lara and Labrador 2013).

Coherently with the literature reported above, the research here proposed is based on the application of HAR technology in the context of agroindustry, with the objective of exploiting the information gathered by a smart sensing device worn by the operators as a part of their standard equipment to improve the health and safety conditions of the workplace. A prototype device, developed specifically for this research, has been employed for gathering and analyzing the vibration data without hampering the activities normally performed by the workers, and to store the pre-processed information in a shared digital layer accessible by all the stakeholders involved in safety surveillance. The novelty of the approach proposed is related to the combination of the activity recognition methodology with a referenced real-time vibration risk assessment approach (Aiello et al. 2012). A real time mapping of the activities performed by the workers and their corresponding risk exposure can thus be obtained in order to promptly undertake preventive or corrective actions when dangerous situations are likely to occur. 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. The average daily vibration is calculated according to the Standard EN ISO 5349-1 (2001), 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 should thus be employed to obtain more realistic values. This research is thus focused on the development of a novel system and related methodology to overcome the above discussed issues by simultaneously mapping the different tasks performed by an operator during its work shift, and the associated vibration dose, thus providing a reliable picture of the inherent operators' exposure to safety risks in real time.

3. Methodology

This section discusses the methodology proposed for mapping the activities performed by a set of operators and at associating their corresponding risk exposure, in order to obtain an overall picture of the safety conditions of a team of workers performing open-field agricultural operations. The methodology proposed is based on the exploitation of could interconnection functionalities and IoT technologies, and can be subdivided into two main steps, namely: the recognition of the activities performed by the operator through a ML classifier, and the assessment of the corresponding hand-harm vibration risk exposure. The general framework of the methodology proposed is depicted in fig. 1, while the specific phases are discussed in detail below. The general framework refers to the open-field operations performed by a team of workers in in the agricultural and forest sector by means of machineries and vibrating tools (e.g. harvesting, pruning, cutting, etc.). During operations, the tools employed generate vibrations that are transmitted to the operator's hand-arm system, thus originating a substantial risk exposure to vibrations. As depicted in figure 1, according to the framework proposed, such vibrations are gathered into two separate data-streams by means of two accelerators fixed to the wrists of each operator, and processed in order to recognize the activity performed and to associate the corresponding risk exposure.

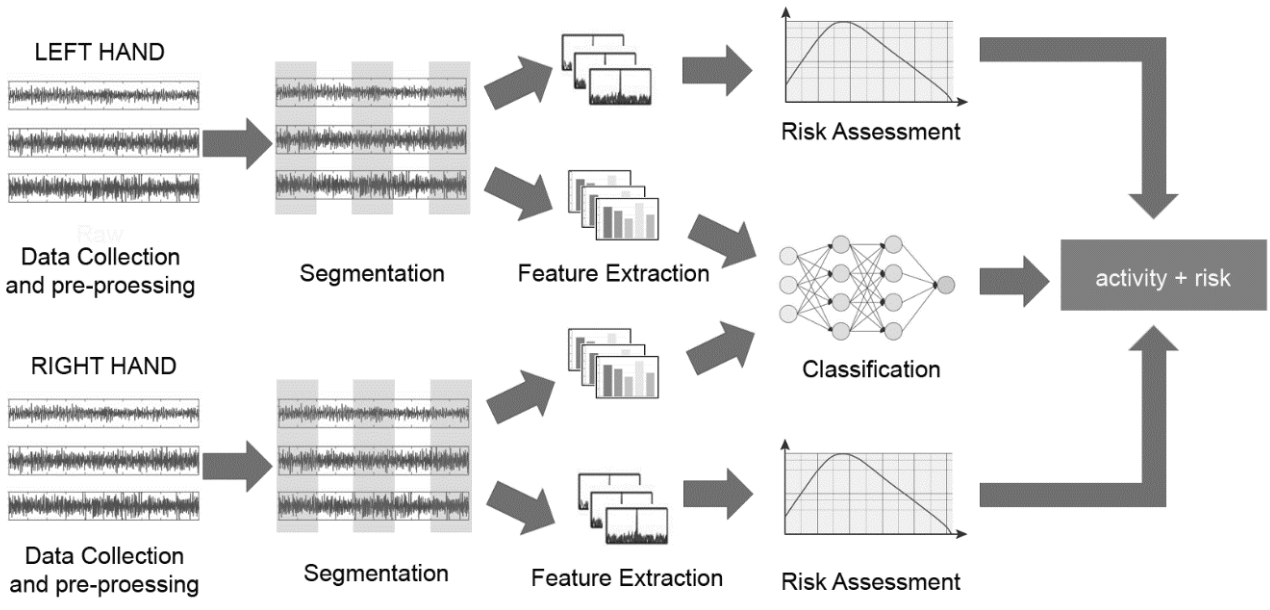

Fig. 1- general framework of the approach proposed

3.1 Recognition and Classification of worker's activity in agriculture

The classification of the activities performed by agricultural workers is based on the analysis of the vibration signals, acquired by a sensor system worn by the operator, through the implementation of a typical Activity Recognition Chain (ARC) of HAR systems (see e.g. Bulling et al 2014). According to this approach, during the initial data collection step, the input vibration data gathered by a sensing device are validated, pre-processed and subdivided into time-segments of fixed length. After segmentation, a set of relevant features is extracted from each data segment and fed into a machine learning classifier for categorization into a set of pre-established classes. In this research, data collection has been performed by means of a wearable prototype device attached to the waist of the operator and cable connected to two advanced tri-axial accelerometers, fixed to his wrists. The tri-axial acceleration data are then instantly recorded for each hand, 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, is strictly related to the polling frequency, which must be therefore accurately defined considering the technical limitations of the hardware employed. After data gathering, the pre-processing step involves all the operations required to transform the measurements into valid input data, suitable for the subsequent feature recognition process. The data gathered can in fact be affected by several inconsistencies such as artifacts deriving from partial reading, out-of-range readings, electro-magnetic noise and interferences in the data transfer. Corrupted data are repaired, thus obtaining regular triplets stored into time-stamped vectors. The subsequent step involves the subdivision of the vibration data streams into time-windows of fixed length, with the aim of reducing the computational effort required for extracting the relevant features. Processing the overall datasets may in fact result in significant delays, particularly when real time applications are performed through embedded systems with limited hardware capabilities (Ravi et al 2016), as in the case here considered. The length of the segments thus generated must appropriately established considering the specific application, being generally recognized that longer time windows improve the accuracy of the recognition process but result in increased computational effort for feature extraction. A detailed discussion on such topic can be found in Banos et al. (2014), however referring to the analysis of vibration levels, Preece et al. (2009) and Dehghani et al. (2019) observed that existing studies generally do not consider time segments exceeding 10s, with polling frequencies mostly varying between 20Hz and 100Hz. Such values appear quite limiting nowadays, since modern CPUs easily allow to process bigger amounts of data in short times. The sensing device employed in this study, for example allowed to seamlessly process data segments of 40 secs in (quasi) real time at a frequency up to 1600 readings per second. Once the gathered data have been segmented, a feature extraction procedure has been implemented to transform the raw-data segments into a restricted set of numerical values. The feature extraction process is thus essentially a dimensionality reduction process, aimed at mapping the original data-sets into a feature-space through appropriate numerical methods. The choice of an appropriate set of meaningful features is of critical importance in this phase to preserve the inherent knowledge for an accurate classification process, while unnecessary features only increase the computational effort without significantly improving the final result. In the case here considered, similarly with several referenced works a set of seven time domain features have been extracted for each axis in each window (table 1), involving statistical attributes frequently employed in the literature (see e.g. Erdas et al. 2016) such as mean, standard deviation, as well as envelope metrics such as maximum and minimum, root mean square, skewness, kurtosis of the signal.

Feature name	**Formula**
Mean	$\bar{x} = \sum_{x_i \in W} \frac{x_t}{N}$
Standard deviation	$\sigma = \sqrt{\frac{\sum_{t=1}^{N}(x_t - \bar{x})^2}{N}}$
Maximum	$Min = \underset{x_t \in W}{\mathrm{mtn}}\{x_t\}$
Minimum	$Max = \max_{x_t \in W}\{x_t\}$

Root Mean Square	$RMS = \sqrt{\sum_{x_t \in W} \frac{x_t^2}{N}}$
skewness	$S = \frac{1}{N}\left[\frac{\sum_{t=1}^{N}(x_t - \bar{x})}{\sigma}\right]^3$
Kurtosis	$K = \frac{1}{N}\left[\frac{\sum_{t=1}^{N}(x_t - \bar{x})}{\sigma}\right]^4$

Table 2 – Time domain Features extracted for activity recognition, *W*=generic data window, x_t generic data value belonging to the segment.

Finally, the last step of the activity recognition chain consists in the classification process, aimed at discriminating the segments into one (binary classification) or more (multiclass classification) categories. The classification problem here considered has 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. 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 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, this value is generally established empirically by a trial and error.

3.2 Risk evaluation

Besides the classification of the operator's activities the methodology proposed involves the evaluation of the hand-arm risk exposure associated to the operations performed by the operator. For such purpose the procedure established consists in analyzing the vibration data after the segmentation step according to the guidelines provided in ISO 5349-1 (2001) and ISO 5349-2 (2001), which relate the vibration dose transmitted to the operator's hands 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 analyzed in 1/3 octave bands. Subsequently, the root mean squared (rms) intensity in each band is calculated and multiplied by an appropriate weighting factor related to the corresponding physiological effect. The frequency weighted acceleration can thus be calculated according to the following equation:

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

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 then 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 threshold finally depends upon the magnitude of the total vibration value and the daily exposure expressed in terms of the 8-hour energy-equivalent acceleration or frequency-weighted total vibration value:

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

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

In real time vibration risk evaluation, an effective approach to ease the calculation is to consider an equivalent vibration score (VS) factor, calculated according to eq. 4.

$$VS = a_{hw} \cdot T^2 \quad (4)$$

The employment of the vibration score allows to update the worker's risk exposure level at each new data segment acquired, and the assessment of the vibration exposure of the operator can thus be undertaken by comparing the instantaneous vibration score with the action threshold and maximum allowable dose, coherently calculated according to eq. 5a and 5b (Aiello et al., 2019).

$$VS^{action} = 8 \cdot 5^2 = 200 \quad (5a)$$

$$VS^{maximum} = 8 \cdot 2.5^2 = 50 \quad (5b)$$

4. Experimental analysis

To validate the proposed methodology, an experimental analysis has been carried out by monitoring a team of operators involved in a mechanized olive harvesting task, with the objective of recognizing the activities performed and determining the related risk exposure. The vibration signals streams generated during the activities performed by the workers have been gathered by means of the wearable device previously mentioned which is based on the Raspberry PI4 "system-on-chip" platform and features a 1.5 GHz 64-bit quad core ARM Cortex-A72 processor, 4GB RAM, WLAN and full gigabit ethernet interface card, integrated in a single board. The wearable device employed is the evolution of a previous system (Aiello et al., 2012) with increased computational capability and improved sensing capabilities provided by the high-performance Bosch BMI160 accelerometer. The BMI160 is a small low noise 16-bit Inertial Measurement Unit (IMU) designed for battery-driven devices, featuring a sensitivity configurable between ±2g and ±16g and a maximum Output data Rate (ODR) of 1.6 kHz. The device is powered by a 20000 mAh Li-po rechargeable battery and connected to a WiFi network, which enables the communication with a centralized system. The vibration signals, acquired with a sensitivity of ±8g and at a frequency of1600 Hz during 3 hours of open-field operations performed by a team of workers, have been segmented into windows of 40 seconds containing 64000 values each, and stored in the local memory of the device. The olive harvesting operations monitored during the field tests, generally involved 15 to 20 catches per tree, with an average duration of 5.5 seconds per catch (Aiello et al. 2019). The overall harvesting time for each tree thus amounts at 10 – 15 minutes, with less than 2 minutes of actual shaking time (catch phases) and the remaining period involving auxiliary operations related to the movements of the operator and the re-positioning of the tool (no-catch phases). In such conditions, and assuming an exposure time limit of approximately 30 min, each operator is expected to harvest approximately 15 trees, in around 3 hours of activity. The experimental analysis aims at validating such values through real time observations.

The pre-processing and feature extraction activities are performed locally on the wearable device, as well as the risk assessment calculations. The system is thus structured according to a decentralized architecture, with the wearable devices capable of classifying 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.

Concerning the classification process, the supervised k-nn approach proposed involves a preliminary characterization of the vibration phenomena originated during the catch and no-catch phases. The results of such preliminary characterization are given in the following figures 2 and 3, where the 6 histograms of the absolute X,Y and Z acceleration values for both hands are reported. It can be observed that, due to the different models of shakers employed during the olive harvesting operations, the catch and no-catch phases originate significantly different vibration phenomena, with a more regular pattern during the no-catch phases where the acceleration values are distributed in an interval between 3 and 10 m/s^2 with two little tails. The acceleration values gathered during the catch phases, contrarily, show a much less regular shape, with significantly higher acceleration intervals and a right tail reaching the cut-off value of the accelerometer (8g). The different characteristics of the vibration phenomena, and the consequent substantially different shapes of the histograms, are the main reasons for the establishment of a recognition procedure based on a set of time domain features, involving the basic descriptors of the histogram shape.

A subset of 500 instances (segments) generated during the tests has been preliminarily classified into catch ("C") and no-catch ("NC") activities, through a human-supervised process. Subsequently, to assess the performance of the classifier, 25 unique NC activity segments and 25 unique C activity segments were randomly selected thus obtaining a set of 50 instances. Such set was then randomly subdivided into a training and a validation set of 40 and 10 instances, respectively and fed into the k-nn classifier. Such random sampling process was iterated 20 times, thus performing 1000 overall classifications with different training sets.

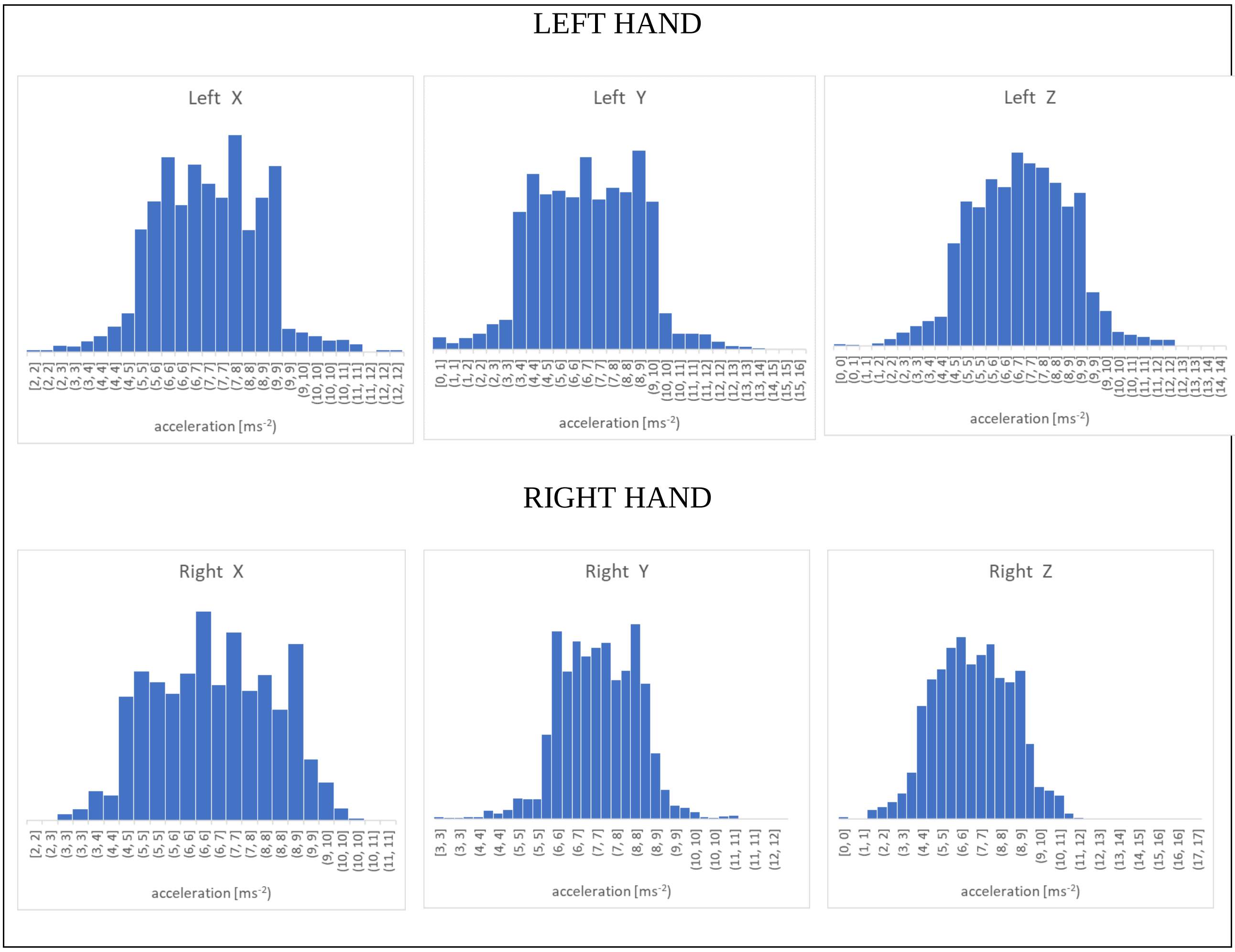

Fig 2 - Vibration histograms related to the no-catch activities

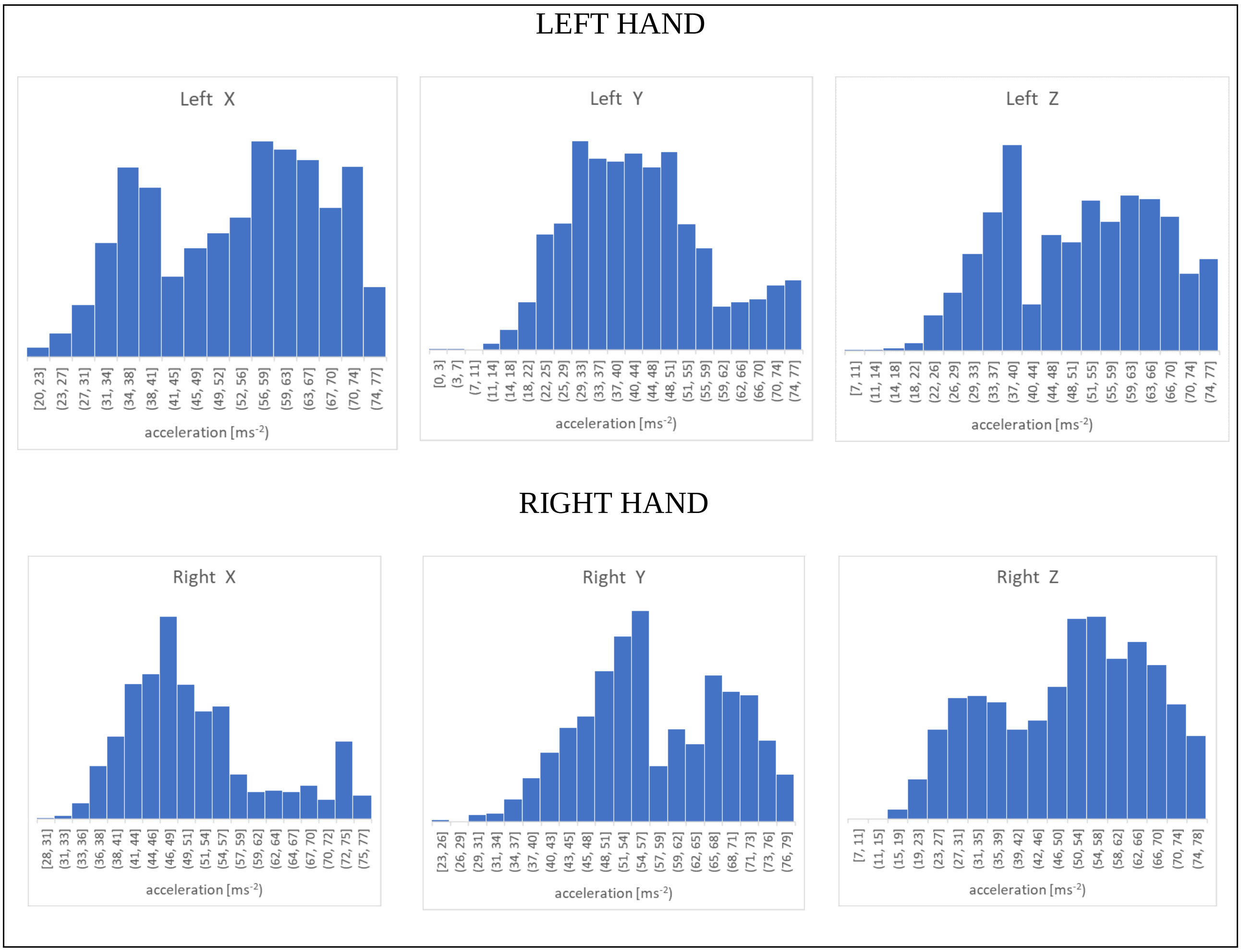

Fig 3 - Vibration histograms related to the catch activities

The accuracy of the classification has then finally evaluated according to the parameters reported in the following eq. 6 to 9.

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

$$Sensitivity\ = \frac{TP}{TP+FN} \qquad (7)$$

$$Precision = \frac{TP}{TP+FP} \qquad (8)$$

$$F - score = 2\frac{Precision\ X\ Sesitivity}{Precision+\ Sensitivity} \qquad (9)$$

Where *TP* (true positive) is the number of samples correctly attributed to the C class and *TN* (true negative) is the number of instances correctly attributed to the NC class. *FP* (False Positives), and *FN* (false negatives) are referred to misclassified instances. The classification results. given in table 2, were thus obtained considering different values of k (5, 7, and 9), in order to analyze the influence of this parameter on the accuracy of the classification, and to choose the optimum value.

	K=9				K=7				K=5			
run #	Accuracy	Sensitivity	Arecision	F-Score	Accuracy	Sensitivity	Arecision	F-Score	Accuracy	Sensitivity	Arecision	F-Score
1	90%	100%	75%	0,86	100%	100%	100%	1,00	90%	100%	75%	0,86
2	90%	100%	80%	0,89	90%	100%	50%	0,67	100%	100%	100%	1,00
3	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
4	90%	100%	80%	0,89	100%	100%	100%	1,00	100%	100%	100%	1,00
5	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
6	90%	100%	80%	0,89	90%	100%	83%	0,91	100%	100%	100%	1,00
7	100%	100%	100%	1,00	90%	100%	88%	0,93	90%	100%	75%	0,86
8	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
9	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
10	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
11	100%	100%	100%	1,00	100%	100%	100%	1,00	90%	100%	83%	0,91
12	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
13	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
14	100%	100%	100%	1,00	100%	100%	100%	1,00	90%	100%	86%	0,92
15	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
16	90%	100%	75%	0,86	90%	100%	83%	0,91	100%	100%	100%	1,00
17	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
18	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
19	90%	100%	83%	0,91	100%	100%	100%	1,00	90%	100%	75%	0,86
20	100%	100%	100%	1,00	100%	100%	100%	1,00	100%	100%	100%	1,00
	97%	**100%**	**94%**	**0,97**	**98%**	**100%**	**96%**	**0,98**	**98%**	**100%**	**95%**	**0,97**

Table 2 performance of the classifier.

The results show that the classifier achieves an extremely good performance level, with an accuracy between 97% and 98%, a sensitivity of 100%, a precision ranging between 94% and 96% and an F-score between 97% and 98%. Additionally, the classification errors were all false positives, while no false negatives were reported. In addition, increasing the value of k from 5 to 9 did not significantly affect the performance of the classifier. With such results, the performance of the classifier can be considered fairly good for the purposes of the research.

Finally, the vibration risk associated to 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. 4 where the vibration streams of the right-hand X, Y and Z axes are given (down sampled to 1 Hz frequency), together with the real time evaluation of the vibration points, and the segments identified as catch activities are indicated in red and the segments related to no-catch activities are indicated in green. The data are referred to a task involving 18 catches performed in approx. 800 secs, with an overall catch time determined by the activity classifier equal to approx. 100 secs, and a risk exposure of approx. 25 points.

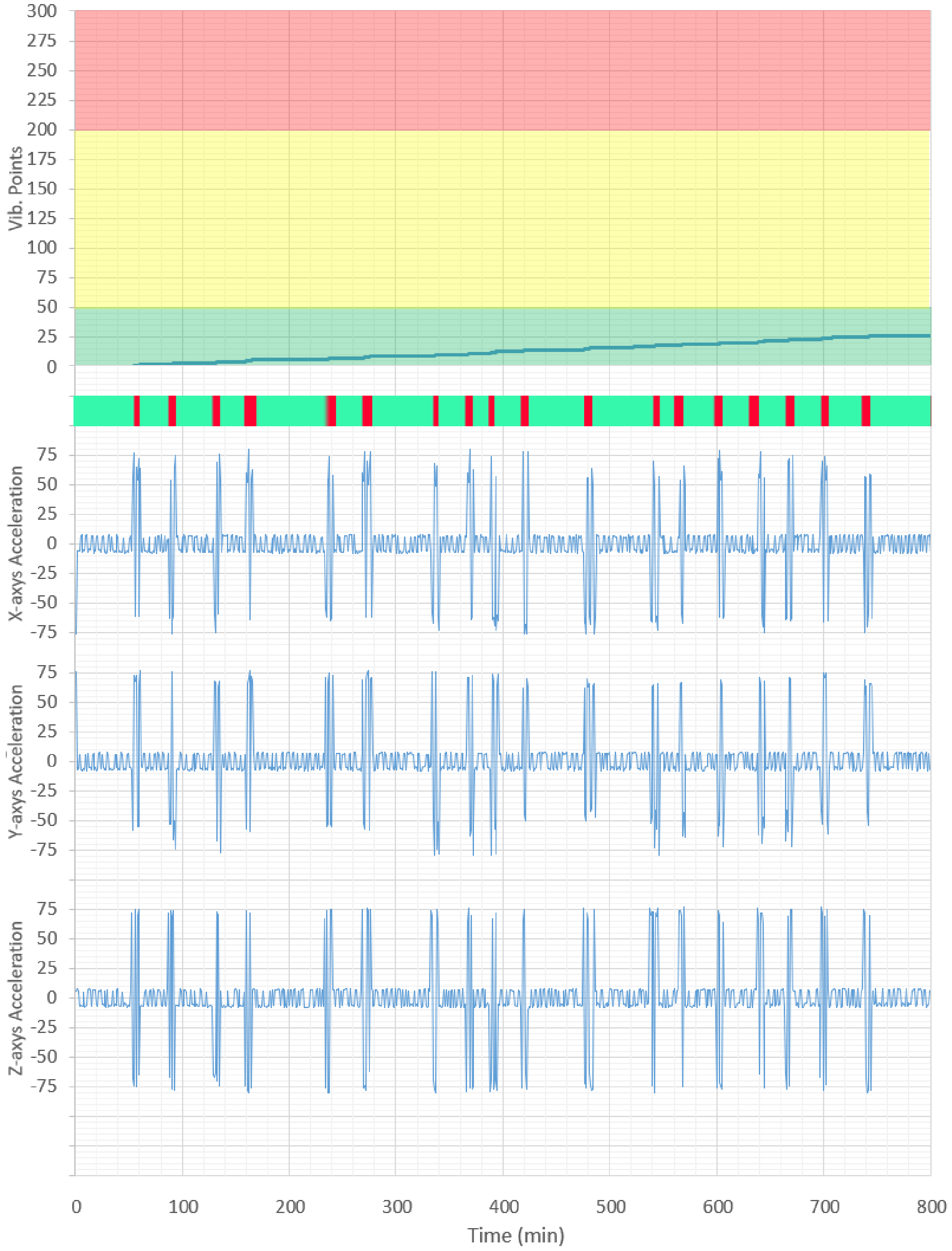

Fig 4 – Map of the activities performed during a task and corresponding worker's exposure to vibration risk.

While encouraging results are being achieved in the application of machine learning classifiers in the context of ergonomics and safety in high-risk contexts such as construction and industrial manufacturing (see e.g. Akhavian 2016), the application of such methodology coupled with a risk assessment method in agro-industrial context is a novel and challenging research field. The peculiarity of the machines employed as well as the execution of open filed operations in isolated contexts, arise specific difficulties in agroindustry compared to their industrial counterparts. Nevertheless, the research proposed demonstrated that modern technologies are mature enough to develop miniaturized integrated devices capable of providing sufficiently precise data, while the KNN algorithm has revealed a robust and versatile classifier, combining a good accuracy with a limited computational effort.

5. Conclusions

Safety and wellbeing are a primary concern in the agroindustry sector, where operators are still frequently performing their activities in an uncomfortable, stressful, or dangerous environment. Furthermore, with the advent of agriculture 4.0 new challenges in the context of human-machine interaction arise, posing ergonomics and safety on the workplace at the core of a substantial multidisciplinary scientific debate. In addition, such problem assumes a critical relevance in consideration of the ageing phenomenon which affects most of the organizations in industrialized countries, with the consequent reduction of the operators' physical and cognitive capabilities.

This research proposes a new methodology for preventing musco-skeletal pathologies related to hand-arm vibrations in the agricultural sector. The approach proposed 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 demonstrates the effectiveness of employing a k-nn classifier for recognizing the workers' activities through the features extracted from the vibration signals gathered during their operations, and the possibility of obtaining a realistic map of their corresponding risk exposure. A wearable device has been developed for the purposes of this research, capable of transmitting relevant information about the workers' safety conditions taking advantage of IoT technologies in an interconnected work environment. The system and the methodology have been validated in real field tests involving a team of workers performing aided olive harvesting tasks. The results obtained demonstrate the effectiveness of the methodology proposed with an overall accuracy of the classifier up to 98%. 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. The proposed research ultimately demonstrates the possibility of providing enterprises with new and more effective systems for monitoring the operators' activities, in order to enhance the health and safety condition of the work environment and to prevent the occurrence of work-related pathologies.

Further developments will involve the introduction of a multi-class classifiers to extend the capabilities of the system, to the recognition of a higher number of activities typically performed in the agroindustry sector. Finally, the implementation of predictive analytics can improve the decision processes related to workforce scheduling and task assignment.

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Declaration of interests

☐The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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