Self-Similarity Matrix of Morphological Features for Motion Data Analysis in Manufacturing Scenarios

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Abstract: There is a significant interest to evaluate the exposure that operators are subjected throughout the working day. The objective evaluation of occupational exposure with direct measurements and the need for automatic annotation of relevant events arose. Using time series retrieved from inertial sensors, this work proposes a method that is able to automatically: (1) detect anomalies, (2) segment the working cycles and (3) by means of query-by-example, identify sub segments along the working cycle. In a short summary, this technique firstly organizes the dataset provided by all inertial measurement units (IMUs) sensors placed over the dominant upper limb. After this, it retrieves a wide variety of features to an organized matrix and then calculates the respective *self-similarity matrix* (*SSM*). This method provides information by comparing each subsequence of the time series with the remaining subsequences. As the identified structures will provide information about how repetitive or anomalous is the behaviour of the data in function of time. The results show that the presented method is capable of identifying anomalies on this dataset with an accuracy of 82%, detect working cycles with a duration error of about 6% of the working cycle, and has the ability to find matches of sub-sequences of the working cycle.

1 INTRODUCTION

Work-related disorders have a global impact on the well being of individuals and their quality of life, as well as being a burden for companies by decreasing productivity, increasing absenteeism and promoting early retirements. More specifically, work-related musculoskeletal disorders (WMSDs) represent a significant portion of the total sum, especially in manufacturing scenarios, where the repetitive nature of the tasks increases the risk of WMSDs (Irastorza et al., 2010). Several strategies have been implemented in large industries to prevent WMSDs and decrease their impact on individuals and companies, namely (1) the inclusion of job rotation schedules that promote a variation of the exposure throughout the working day and (2) the implementation of ergonomic assessment methods that support the evaluation of the occupational risk for a specific workstation (Rodrigues et al., 2020). Nevertheless, the current approaches are far from being optimal in the sense that these strategies might (1) not be automated, depending on observational methods, which requires dedicated personnel to observe or look into video records of operators at work, (2) still rely on subjective opinions, (3) be based on global indicators that do not take into account the variability among the population of operators, namely anthropometric variations, age, working experience, among others and (4) yield to single score to represent the ergonomic risk of a workstation, which is insufficient to explain the factors that contribute to this risk.

All these factors contribute to the high workload that is required in implementing these strategies, hence being very difficult to employ them across

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the complete operator's population at manufacturing sites. With the advent of Industry 4.0, more companies are using new strategies and improving the ones currently applied by the addition of digital industry technology, namely sensors, automation, dedicated algorithms and machine learning methods (Romero et al., 2016).

In this work, we highlight the interest in using inertial sensors to have direct measures for a more specific assessment of occupational risk for each operator. In (Santos et al., 2020), inertial sensors were used to evaluate the occupational exposure of several operators performing different types of workstations. The assessment was based on the RULA screening tool that considers biomechanical and postural load requirements on upper limbs. These are evaluated for each working cycle, which represents the period during which an operator performs a specific set of tasks of a workstation, repeating the cycle of tasks during the working period. Having data signals from wearable sensors that characterize the working period of an operator, there is more control and flexibility on the time periods that are selected for assessment. This has several benefits because it is possible to (1) make objective assessments for each working cycle, understanding how the occupational exposure varies from the first working cycle to the last one; (2) compare, for the same workstation, how was the occupational exposure of different workers; (3) compare the occupational exposure of different workstations performed by the same worker and (4) compare the occupational exposure of subsections of the working cycle, identifying which are the tasks that contribute more for the exposure score on the working cycle. Still, methods for the detection of working cycles and anomalies should be available. With such techniques available, the flexibility and detail of analysis can have a great impact on improving the ergonomic assessment, have better strategies to design balanced workstations and improve the design of job rotation plans. Therefore, the design of algorithms and tools that promote this flexible, quicker and more detailed analysis is of great relevance to achieve the mentioned benefits.

In this work, we propose an unsupervised method that uses the acquired inertial data to (1) automatically detect anomalies in the working period, (2) automatically divide the working period into working cycles and (3) use a sub-segment of the working cycle to identify all the corresponding sub-segments in the working period by means of a query-by-example approach. The method is performed by computing a self-similarity matrix based on the extraction of a list of features of all signals acquired by employing a sliding window process.

The document starts with a review of the related work that shares the same contextual problem. Then, the description of the dataset follows, and a detailed description of the proposed method is presented. The results are then presented and discussed. Finally, we conclude and detail ideas for future work.

2 RELATED WORK

The problems regarded in this work involve essentially the identification of cyclic information and anomalies. Typically, algorithms developed for these purposes may resort to (1) supervised machine learning (ML) methods, which require a certain level of annotation beforehand and (2) unsupervised methods, which are based on the similarity analysis of the signals or their features, without any prior information. Several methods found, employed in the analysis of inertial data, are used in the context of human activity recognition (HAR). The list of supervised ML methods is extensive and promising works are found to achieve this purpose. The application of neural networks (Lara and Labrador, 2013), hidden Markov models (Zhu and Sheng, 2009), decision trees (Jatobá et al., 2008), bayesian networks (Jatobá et al., 2008), and semi-automatic process (Bota et al., 2019), among others, are algorithms capable of detecting and classifying various human actions. Nonetheless, most of the work done in this context only looks to identify previously defined actions like lying, standing, sitting down, move upstairs, etc., that might not be cyclic and rely on a significant amount of labelled data.

Several works that use unsupervised methods for the identification of cyclic information and anomalies are also found. The most simple method of cycle detection is the use of point references on the workplace to describe when a cycle starts and ends. Which is usually considered a system subject to flaws with a requirement for further adjustments steps (Bauters et al., 2014; Bauters et al., 2018). Other more reliable alternatives analyze features of the signal and search for periodic motion in those. An automated algorithm of segmentation was able to separate complex and multidimensional data into smaller segments that can be described through harmonic models. This algorithm revealed to be significantly useful to identify cyclic movement without any *a priori* knowledge of the input data, using a combination of a recursive least squares segmentation algorithm, a model fitting of damped harmonics, and in the end, a clustering analysis to classify the events (Lu and Ferrier, 2004; Lu and Ferrier, 2003). The usage of features is of great relevance in unsupervised works, and methods are found to select adequate features for detection and classification tasks, such as in (Machado et al., 2015). Another example is the use of four-pass UKF (unscented Kalman filter) to produce an unified model with kinematic parameters. These may then be segmented by analyzing the parameter's zero crossing velocity and in the end uses a clustering algorithm to identify repetitive segments (Wang et al., 2015).

Other methods rely on a self-similarity approach, namely (Nunes et al., 2011), where cyclic information is segmented by searching for minimums, in the convolution of a segment of the signal with itself. The *Matrix Profile (MP)*, which is a method that compares all sub-sequences of a given time series with themselves through an euclidean distance, has also revealed promising results. In the end, it returns the minimum value distance for each segment, highlighting the moments of the time series which are similar within themselves (Yeh et al., 2018). Additionally, autocorrelation revealed itself an useful tool, as the search over maximum values can infer the cyclic nature of the data (Bauters et al., 2014). Finally, for anomaly detection in industrial scenarios, an interesting work applies an unsupervised method based on the clustering of time series segments to detect the execution of improper movements (Varandas. et al., 2019).

The following work is inspired over an algorithm for the detection of musical structures on audio signals (Foote, 2000; Paulus et al., 2010; Bello et al., 2018) by means of a *Self-Similarity Matrix (SSM)*. This sort of analysis of self-similarity to collect information about the periodicity has also been performed over video datasets. This type of analysis usually consists on a framework where a Fourier analysis is performed on an *SSM* to characterize and highlight the periodicity of the data from the video (Cutler and Davis, 2002; Cutler and Davis, 1999).

3 DATASET

3.1 Participants

The in-field data used in this work was acquired in the assembly lines of an automotive assembly plant while the subjects were performing the tasks of a specific workstation. The context of the acquisition regarded the validation of an inertial system that would guarantee access to direct measures. These were used to deliver an ergonomic risk assessment based on the angular information retrieved by the raw data of the sensors (Santos et al., 2020). The dataset included six participants, each monitored while working at two different workstations. In this scenario, each workstation has a specific set of tasks that have to be performed by the worker. These tasks are repeated throughout the working period, being divided into working cycles.

3.2 Experimental Setup

The study was conducted by measuring data from the dominant upper limb of the subjects. The system comprehends a set of four 9-DoF inertial motion units (IMUs) with each containing a triaxial accelerometer, gyroscope and magnetometer. The IMUs were attached on the upper dominant limb of the subjects, namely:

- **IMU 1** posterior side of the hand
- **IMU 2** posterior side of the forearm (wrist)
- **IMU 3** posterior side of the arm (elbow)
- **IMU** 4 thorax area

All devices were attached so that the alignment of Y-axis was pointed up. The Figure 1 presents the main configuration of the acquisition setup and device placement.

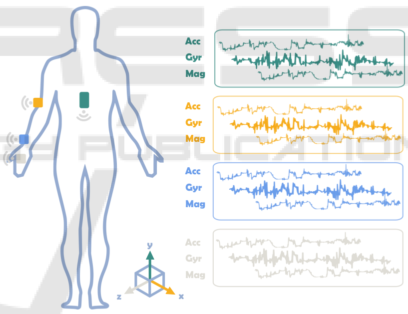

Figure 1: Schematic of the placement of Inertial sensors, used for the dataset acquisition protocol. Based on (Santos et al., 2020).

The signals available for analysis are the 3-axis accelerometer, gyroscope and magnetometer of all IMUs used, collected with a sampling rate of 100 Hz.

These data have multiple working cycles intercalated with resting moments. For the annotation of these events, all signals were annotated by means of video-records of the acquisition sessions.

4 METHODS

Signals acquired during a working period have a periodic nature, since the set of tasks of the workstation are repeated in each working cycle. Therefore, each signal acquired has a recurrent pattern of the

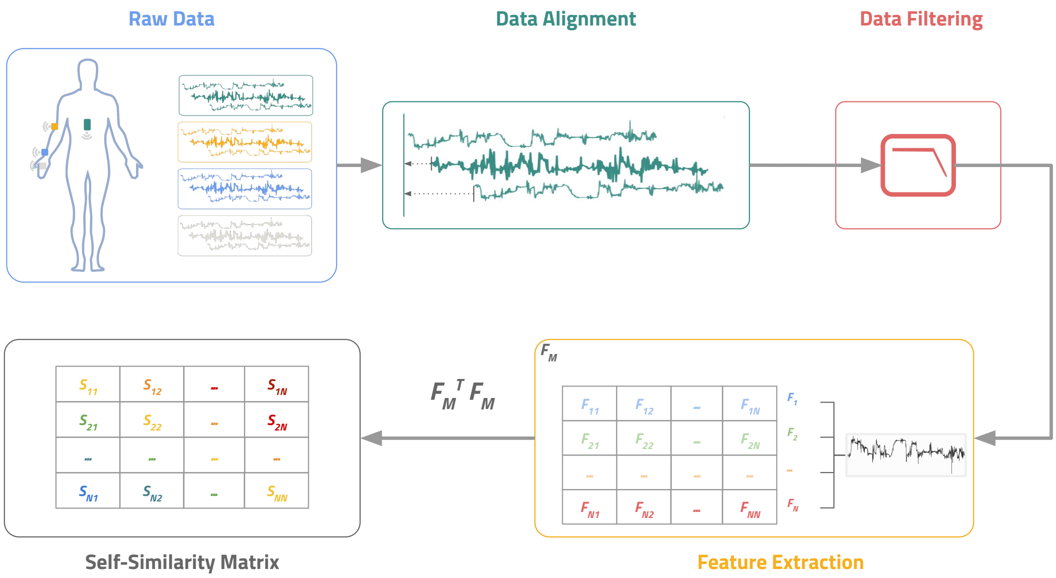

Figure 2: Main schematic of the proposed method.

tasks performed during the working cycle. Nevertheless, being signals acquired in a real working context, unexpected events occur and are present on the signal. Several anomalies can be found, namely (1) when the operator stops working because of a break on the working line, which can be caused by delays on other workstations; and (2) when the operator takes more time to perform a specific task or rather have to make a significant amount of additional motions to perform the working cycle. In this work, we are searching for a method to unveil the periodic nature of the signal and identify dissimilar moments.

The method proposed to identify (dis)similarity on the signals acquired is inspired in a method employed to analyse several dimensions of musical structures, namely homogeneity-based, novelty-based and repetition-based (Paulus et al., 2010). The process involves extracting a set of features that are able to characterize the morphological dynamics of the signal and how it varies over time, and compute a *SSM* based on the features extracted (Paulus et al., 2010). From the *SSM* we are able to extract a relevant set of information.

The sequence of steps to calculate the *SSM* are presented in Figure 2. The first row of steps shows the preparation of the signals, namely the process for data synchronization and alignment between signals of different sensors, and filtering the signals with a second order Butterworth low pass filter with a cut-off frequency of 20 Hz. After the preparation of the signals, the selected list of features are extracted from all signals and organized in a matrix, from which the *SSM* is computed.

4.1 Features Extraction

Extracting relevant features is of great importance to have a rich characterization of the morphology of each signal (Rodrigues et al., 2017). The features were extracted employing a sliding window process. With this method, a set of predefined features are extracted on each segment of the signal, selected in each iteration. The window segment has a predefined size $window_s$ and each iteration proceeds with a predefined overlap percentage $overlap_p$. We used the TSFEL (Barandas et al., 2020) Python library to extract a set of features in the statistical, temporal and frequency domains. We used all the available features except the wavelet-based features to reduce the computational time.

The $window_s$ and $overlap_p$ parameters have a large influence on the results. The first defines the time scale at which features are extracted, therefore the higher is the size of the window, the larger is the time scale at which feature values change. Regarding the second parameter, it defines the resolution of the resulting feature-signal, therefore the higher is the overlap percentage, less information is lost and the higher is the resolution.

After extracting the set of features, these are organized in a matrix F_M. The rows are a feature representation of the signal, and columns represent the characterization of one sample of the signal by all features extracted. The matrix is built with the features extracted from all signals. At last, each extracted feature is z-normalized.

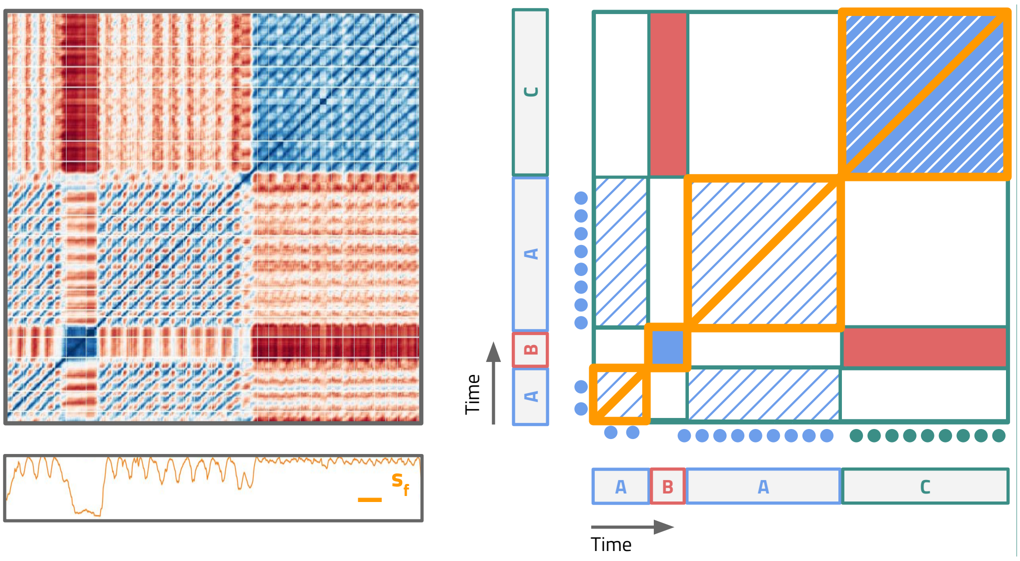

Figure 3: At the left is the *SSM* designed from the signals acquired while an operator was performing 2 different workstations. At the right is a simplification of the original *SSM*, with highlights on the main structures present. Additionally, the orange signal on the left plot is the similarity function, calculated by summing the values of the *SSM* column-wise.

4.2 Self-Similarity Matrix Analysis

The purpose of the *SSM* is to compare each sample of the signals with all the other samples. In order to calculate the *SSM*, the dot product between the transposed F_M and itself is performed. Therefore, each column of the matrix is compared with each other, giving a similarity score. Columns that have feature values in common have higher similarity scores, while columns with diverging feature values will have lower similarity scores (Paulus et al., 2010; Bello et al., 2018). Each column of the matrix represents the characterization of each segment of the signal that was selected during the sliding window process. By comparing each column of the matrix with each other, we are comparing each segment of the signal with each other, hence creating a matrix that provides a rich visual information about how the signal is structured and how it behaves over time.

In Figure 3 are illustrated the standard structures encountered in a *SSM* (Paulus et al., 2010):

(1) Main Diagonal - The main diagonal is a result of comparing each column of the transposed matrix with the rows of the original matrix that correspond to itself. The values of the main diagonal are the highest similarity values;

(2) Blocks - Block structures represent areas of the signal with an homogeneous behaviour. When a block structure changes into a different block structure along the diagonal, it means the behaviour of the signal changed. These structures help in identifying significant changes in the signal. For instance, in Figure 3, **block A** changes to **block B**, then to **block A** and finally to **block C**. These blocks are highlighted in orange;

(3) Secondary Diagonals - As mentioned, the main diagonal is created by comparing each column of the matrix with itself. When other diagonals are visible in the matrix apart from the main one, we can infer that the columns and rows of the matrix segmented by the secondary diagonal have similar properties. These structures are therefore a way of detecting reoccurring patterns of the signal. For instance, in Figure 3, secondary diagonals on **blocks A** and **block C**, indicate that segments A and C are periodic. Additionally, the pattern repeats on the instant the secondary diagonal starts, which is indicated by colored circles under each segment.

From the *SSM*, we can extract the required information by applying several methods. For the identification of anomalies and the segmentation of working cycles, we based the method on computing the similarity function, which represents the column-wise addition of values from the *SSM*. Regarding the selection of similar sub-sequences of the working cycle, we used a query-match by example approach on the *SSM*, where the example is the selected sub-sequence of the matrix. These methods will be further detailed in the following subsections.

4.3 Anomalies and Working Cycles Segmentation

Anomalies are, in this context, defined as being dissimilar segments of the signals in comparison to the average working cycle. These anomalies during the working period will be assessed by means of identifying the similarity levels in the signals with the similarity function. The similarity function, *sf*, is calculated by summing the values of the *SSM* column-wise, being each element of the *sf* calculated by:

$$s_f(x) = \sum_{i=0}^{N} SSM_{ix} \quad (1)$$

where *j* the column position for the sum, sf_j the sample of the function at position *j* and *N* the size of the *SSM*.

This function provides information about how similar each sample of the signals is with the remaining signals, therefore if samples belong to an anomaly segment, the similarity values for the corresponding column on the matrix will be lower. Therefore, the sum of similarity values will also be lower than for other segments of the matrix. With this process, segments of the similarity function with lower values indicate the presence of the mentioned anomalies. This can be visualized in Figure 3, where **block B** of the *SSM* are associated with the lower values in the s_f representing an anomaly.

Regarding to periodic signals, the sample values of the similarity function will be very similar for equal moments of each period, therefore creating a repeating pattern of similarity, which can be used to segment working cycles. The process involved three stages: (1) remove the anomalies, identified with the previous method; (2) recompute the similarity function with an *SSM* without the selected anomalies and (3) use a peak detector to identify the cycles.

As previously mentioned, secondary diagonals indicate the presence of similarity and reoccurring patterns can be visualized on the *SSM*. The starting point of these diagonals corresponds to the position at which the cycle starts. By removing the encountered anomalies, we can reject lower areas of the similarity function, unveiling the periodic pattern of similarity. The resulting similarity function has a prominent minimum at the position where diagonals start. Finally, to segment and divide the working period in working cycles, we have to identify the local minimums of the function. This is illustrated in Figure 3 where the s_f has repeating local minima at the position where the secondary diagonals start, on **blocks A**.

4.4 Sub-segment of Working Cycle Search

Another relevant purpose for the evaluation of the occupational exposure in industrial scenarios is to compare the occupational risk of sub-segments of the working cycle during the working period. As mentioned, this strategy helps professionals in identifying which sequence of tasks of the working cycle are more responsible for the occupational risk, and help them understand if a workstation needs to be adapted, i.e. having a more balanced set of tasks.

In this case, the search procedure is aided by signalling the desired sub-sequence in the signal, which is given as an argument in the function. The search procedure works by sliding the smaller column window (the example selected) along the *SSM*, one sample at a time. The distance, *D*, between the example and the segment it slides over is calculated through the sum of absolute differences:

$$D(x) = \sum_{x=0}^{x=M} \sqrt{(SSM(x) - SSM_t)^2} \quad (2)$$

where $SSM(x)$ the segment of the *SSM* over which the example, SSM_t, slides at moment *x*, starting from 0 to the size of the *SSM*, *M*. The resulting function has minimums at the position where the example is matched, as presented in Figure 4.

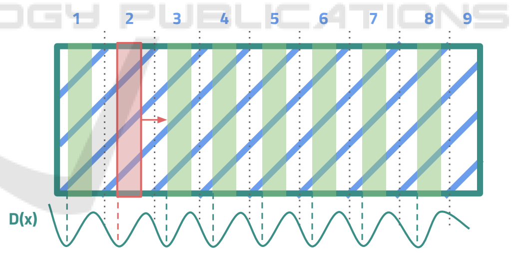

Figure 4: The Figure illustrates a simplified representation of a block structure of an *SSM*, with repeating secondary diagonals. The cycles are represented by order and their corresponding numbers, while also divided by the dotted lines. The red highlighted segment represents the selected example of the working cycle to match along the other periods of the matrix. The green highlighted areas represent the perfect match along diagonals and has, therefore, a minimum in the distance function ($D(x)$).

5 RESULTS AND DISCUSSION

In this section are presented the results of applying the algorithm to the dataset for discovering anomalies, working cycles and sub-sequence search. We present an example of applying the proposed method to one of the acquisition sessions, whereas global results will be shown for the entire dataset in Table **??**.

5.1 Working Periods Identification

The detection of anomalies involved searching for areas with lower similarity. The areas with lower similarity would represent segments of the working period in which the operator would have different motion information than the most common during work. These can correspond to the mentioned anomalies.

Table 1: Results of the detection of the mentioned anomalies. The workstations (Wkstn) with no indicators reveal no anomalies. Operator 6 was not considered because the videos for the activity recorded only the beginning of the task. TP-True Positives, FP-False Positives, FN-False Negatives and A-Accuracy. TP, FP and FN are measured with a resolution of seconds. (TN - True Negatives are not considered to not bias the results).

Signal	Wkstn	Detected	TP	FP	FN	A(%)
Operator 1	1	3/3	268	1	140	65.53
	2	1/2	45	0	17	72.5
Operator 2	1	2/2	305	0	6	98.07
	2	-	-	-	-	-
Operator 3	1	0/1	0	0	50	0
	2	-	-	-	-	-
Operator 4	1	2/2	488	22	0	95.69
	2	-	-	-	-	-
Operator 5	3	1/2	49	0	19	72.05
	4	1/1	71	0	2	97.26
All		10/13	1226	23	234	82.67

Table 1 shows the results of applying a threshold based method on the similarity function. Values under the threshold would be considered anomalies of the working period. The results are presented in terms of how many anomalies were identified per working period as well as how accurate was this detection, in seconds, based on the values of TP, FP and FN.

Results show that the algorithm is able to detect the majority of the anomalies. In cases where the anomalies were short, the detection would not be possible. This might be a resolution problem, considering the window used to extract the features from the signals, but further investigation should be made. The error rate of the detection is still significant and is also related with the resolution issue. Nevertheless, the overall results are promising for using this technique for these scenarios.

5.2 Working Cycles Identification

We applied the method of detecting the working cycles by analysing the *SSM*. We evaluated the capabilities of the algorithm by comparing its performance with a well known algorithm proven to work in similar problems, the *Matrix Profile (MP)*. We applied the *MP* algorithm to one signal of each acquisition dataset. The *MP* algorithm receives only one parameter that defines the time scale of the repeating pattern. For each session, the average size of the working cycle was taken into consideration for the usage of the *MP* algorithm. We used the implementation of the *MP* algorithm from *stumpy* (Law, 2019). Both the MP and *SSM* algorithms have their performances evaluated in terms of:

(1) **Correct Detection of Cycles.** A cycle segment is considered correct if the moments at which the cycles are segmented correspond to a consistent position on the signal. Even if the segmentation of cycles occurs delayed from the ground-truth selection, what is evaluated in this category is the consistency of the algorithm in defining the working cycle. Here are measured how many cycles are correctly segmented;

(2) **Calculate the Error between the Ground-truth Segmentation and the Algorithm's Segmentation.** The ground-truth duration of cycles is compared with the duration of the detected cycles by calculating the absolute difference between durations. This error is expressed in terms of seconds per cycle and duration percentage of the cycle. In Figure 5, the left plot illustrates an example of segmenting the working cycles by means of the similarity function. The *SSM* function was calculated by a set of features extracted with a time window of 50 seconds and an overlap of 85%. The similarity function was smoothed with a moving average window of 20 seconds. The first figure of the right plot shows the ground-truth segmentation, and the second figure the segmentation based on the similarity function.

Results presented in Table **??** show that the methods tested have equivalent performance to detect working cycles in industrial data. Most cycles were correctly detected by both algorithms, although there is a delay in the detection. This delay is comprehensible considering that the algorithm, being unsupervised, does not have a reference of where the cycle has the ”real” start. The algorithms take into consideration the beginning of the data as a reference, which would not always match with the instant the operator would start the cycle. The lag detected does not have an effect in the detection of the entire cyclic information, since both algorithms are consistent with their decision of where the ”start” is, and are able to identify the cyclic pattern. Moreover, they have a similar

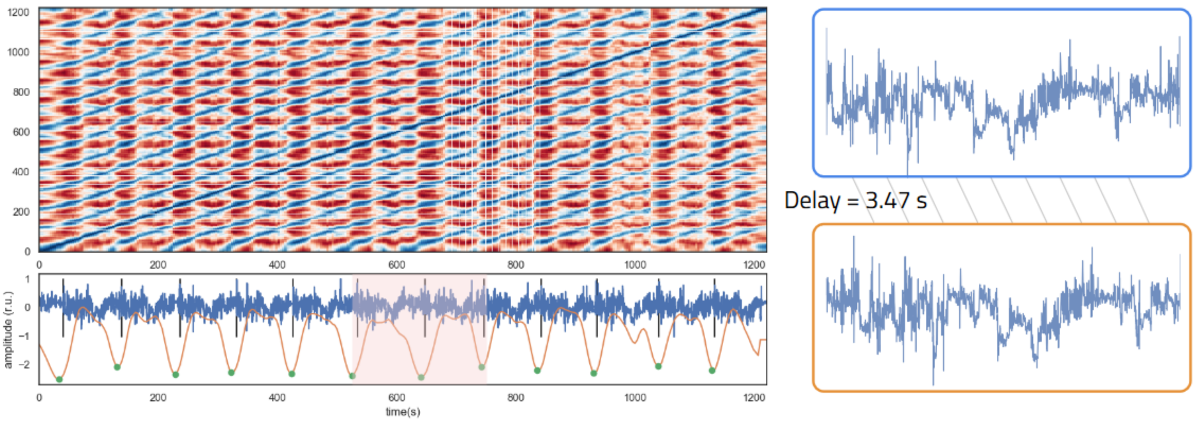

Figure 5: Example of the detection of working cycles by means of the *SSM* after removing the anomalies. Black bars represent the ground truth events, green circles are the detected cycles on the similarity function (orange), represented on the bottom subplot. The X-accelerometer signal from the hand sensor is in blue.

Table 2: Results of searching for minimums in the similarity function, calculated based on the *SSM*. The proposed method is compared with the *Matrix Profile*, by means of number of cycles detected and duration error.

Signal	Workstation	Cycles	*SSM*		*Matrix Profile*	
			Cycles	Duration Error	Cycles	Duration Error
Operator 1	1	11	11	3.26s (3.04%)	11	11.08s (10.34%)
	2	15	14	16.97s (15.83%)	14	8.09s (7.55%)
Operator 2	1	14	14	6.45s (6.40%)	14	6.74s (6.70%)
	2	11	11	8.48s (8.62%)	11	11.2s (11.39%)
Operator 3	1	16	16	12.35s (11.79%)	16	7.39s (7.05%)
	2	13	13	8.81s (8.25%)	12	11.41s (10.68%)
Operator 4	1	14	14	1.05s (0.4%)	14	8.72s (8.24%)
	2	11	11	3.42s (3.32%)	10	4.9s (4.75%)
Operator 5	3	12	12	2.83s (2.85%)	11	5.39s (5.43%)
	4	10	11	3.47s (3.45%)	10	6.7s (6.69%)
Operator 6	5	15	14	3.79s (3.74%)	15	7.25s(7.15%)
	6	15	14	5.79s (5.73%)	15	6.13s (6.06%)
All		157	154	6.12%	154	7.6%

performance in this regard.

The proposed algorithm also shows that it works for several scenarios, namely different types of workstations made by the same worker as well as different workers making the same workstation.

The duration error is mostly good as well, but still significant in some of the cases. The duration was calculated to be an indicator of the detection quality. Even in cases where the detection is delayed from the ground-truth annotation, the duration of the working cycles should be the same. On average, the error represents 6% of the working cycle, which can be up to 6 seconds in working cycles of 100 seconds. This error might have contributions from the loss of resolution when extracting features, smoothing the similarity function to detect the minimums and errors in the manual annotation of the events. Nevertheless, the results are promising, showing that the algorithm is able to segment the working cycles of a working period.

The difference in performance between the *SSM* method and the *Matrix Profile* are not significant. The slight difference in duration error might occur because of the smoothing factor used with *Matrix Profile*, which was higher, and therefore increased the chance of errors in the duration of the working cycle. Nevertheless, both had equal performance in dividing the working period into cycles.

5.3 Sub-segment Search

In the example presented in Figure 6 is demonstrated how the *SSM* can be used to identify sub-segments of the working cycle during the working period. The detection is based on the match of columns (or diagonals), which results in a precise matching function. The orange signal represents the similarity function to demonstrate that the minimum values of the distance function are consistent with the cycle position. Highlights are used on the image starting at the exact minimum position, which is the place where the sub-segment being searched starts.

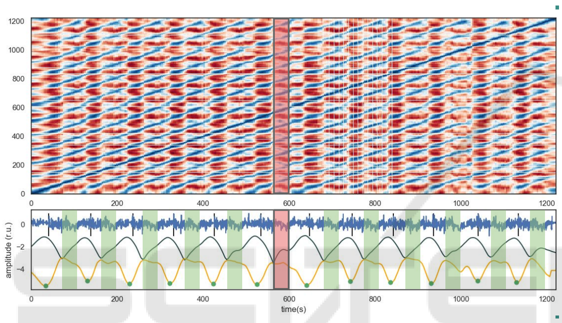

Figure 6: Example of sub-segment search on the *SSM*. The *SSM* is presented in the upper plot, with a sub-segment highlighted between cycles 5 and 6. The blue signal is the X-accelerometer of the hand sensor, the orange signal is the similarity function and the grey signal represents the distance function. The red segment highlighted is the example used to compute the distance, and the green segments are the matches based on the distance function.

5.4 Overview

The results show that the *SSM* is fit for the problems in demand. This method has the advantage of relying on characteristics of the signal, giving a rich insight about the signals being analysed. Additionally, using this method enables the use of a multisignal approach, not relying on the information extracted from a single signal for the analysis of the entire dataset, or having to analyse all signals individually to match the information. Nevertheless, further tests should be made to understand the clear benefits and disadvantages of using a multisignal approach.

This method also has the advantage of giving solutions to several questions at once. In this case, from the *SSM* we were able to identify anomalies, search for the cyclic pattern underneath the data and make a sub-sequence match.

6 CONCLUSION AND FUTURE WORK

In this work, we demonstrated that the application of the proposed method on motion signals acquired in cyclic tasks of the industrial context is possible. The proposed method was able to identify (1) anomalies during working periods, (2) segment the working period in working cycles with similar performance to the *MP* algorithm and (3) search for sub-segments of the working cycle along the working period. The application of this method in the ergonomic context can be of great interest since it can improve the current approaches of ergonomic evaluations in these scenarios. This strategy turns the process more flexible, allowing to identify in the working cycle sources of risk factors. Moreover, this allows not only to compare the occupational exposure of different workstations for the same worker but also to compare the occupational exposure throughout the working period. Furthermore, our method has the potential to decreases the workload associated with the manual identifying of working cycles and anomalies while improving the accuracy of the evaluation.

The proposed method is promising and further investigation should be made. Improvements can be made, namely: (1) the size of the *SSM* can cause memory errors for signals with a large number of samples, increasing the memory by a quadratic function, and this should be optimized; (2) having to perform the extraction of a significant number of features turns the process slower, so features should be targeted for the type of signal being analysed; (3) because of (1) and (2), it was more indicated to not use a total window overlap, losing resolution and (4) further research should be made in the usage of multisignals.

The methods used to extract the overall information from the *SSM* can still be improved. The detection using the similarity function is prone to some errors, as presented in the results, and better methods can be developed in further research to identify the presence/absence of diagonals. Eventually, methods inspired in image processing could be used.

Finally, the *SSM* could also be used to search for relevant transitions between blocks. For instance, In Figure 3, we can visually identify two different blocks of repeating cycles, therefore the *SSM* can be used to detect transitions between workstations as well.

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