Evaluation of Spatial-Temporal Anomalies in the Analysis of Human Movement

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Abstract: In industrial contexts, the performed tasks consist of sets of predetermined movements that are continuously repeated. The execution of improper movements and the existence of events that might prejudice the productive system are regarded as *anomalies*. In this work, it is proposed a framework capable of detecting anomalies in generic repetitive time series, adequate to handle human motion from industrial scenarios. The proposed framework consists of (1) a new unsupervised segmentation algorithm; (2) feature extraction, selection and dimensionality reduction; (3) unsupervised classification based on Density-Based Spatial Clustering Algorithm for applications with Noise. The proposed solution was applied in four different datasets. The yielded results demonstrated that anomaly detection in human motion is possible with an accuracy of $73 \pm 19\%$, specificity of $74 \pm 21\%$ and sensitivity of $74 \pm 35\%$, and also that the developed framework is generic and may be applied in general repetitive time series with little adaptation effort for different domains.

1 INTRODUCTION

Anomalies consist of events that do not properly conform to the expected behaviour of a given dataset. Anomaly detection has been widely studied and applied in diverse domains, such as electrocardiogram (ECG) signals, video from surveillance cameras and stock markets (Chandola et al., 2009). The importance of anomaly detection lies in the fact that such events are usually associated with defective processes that might cause failures in the future. Taking the example of ECG signals, anomalies might be associated to cardiac arrhythmias, which may be an early or actual indicative of heart diseases.

The increasing demands of Industry 4.0 require highly customised products and adaptive manufacturing systems. The detection of unplanned or planned anomalies in Human movement on industrial production lines is a valuable asset for production control systems. This information is able to deliver intelligence regarding occurrences that might prejudice the productive process, reducing the overall productivity and compromising ergonomics and safety at work. Furthermore, the monitoring of human motion in such environments allows to detect predetermined movements that the operators are instructed to follow in order to improve production and ergonomic conditions. Therefore, an anomaly may consist of wrongly performed movements, which may prejudice ergonomic conditions and improve the risk of appearance of musculoskeletal disorders.

The Human movement in Industrial scenarios can be monitored using inertial sensors, which provide tridimensional motion information. For each task associated with a given workstation on a production line, there is a well-defined method that must be followed to accomplish it. However, since methods vary according to the workstation, the repetitive inertial data might exhibit different morphologies despite maintaining the quasi-periodic behaviour.

2 RELATED WORK

Anomaly detection has been the target of extensive research and various surveys were already published (Teng, 2010; Chandola et al., 2009).

For instance, HOT SAX is a method based on the SAX representation, developed in (Thuy et al., 2018), to find discords which are sequences that are the most dissimilar to its k nearest neighbours. Therefore, this algorithm, is able to find anomalies in time series, but

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it is necessary to know the number of anomalies to be found *a priori*.

In (Ren et al., 2017), it was developed the PAPR representation method coped with the construction of a Random Walk model with the intent to search for anomalous patterns in time series. The proposed algorithm was tested in 14 different real world datasets and compared with the PAA method, achieving higher results. While PAA method detected 15 anomalies, PAPR associated with Random Walk (PAPR-RW) algorithm was able to detect 25 anomalies out of 27, and so, the sensitivity is approximately 92%.

There are numerous other examples of anomaly detection in time series, such as, network source data (Chen and Li, 2011), gait analysis (Cola et al., 2015), streaming data (Ahmad et al., 2017), ECG signals (Ren et al., 2017), in which arrhythmias may be viewed as anomalies, and detection of mental stress (Huysmans et al., 2018), in which case, stress states may be considered anomalous.

Most mentioned methods, though being adequate for particular applications, lack the capability of being applicable in different domains. Furthermore, the methods that may be applied to various domains, either need high numbers of parameters or the required parameters are difficult to assess, for example the number of anomalies to detect.

This work comprises the development of a novel framework for anomaly detection applied to domain-independent repetitive time series, requiring a low number of parameters to be selected and in which, the parameters have physical meaning, facilitating their estimation. This approach is indicated in our context, because in manufacture environments, different workstations involve different methods, which results in different repetitive patterns. Thus, it is able to cope with different time series domains with minimum adaptation effort. In order to achieve this, our work presents two major contributions: (1) a new unsupervised segmentation algorithm for quasi-periodic time series, which is able to extract repetitive units from those time series, and (2) an unsupervised learning approach that relies on an exhaustive set of features to provide anomaly detection. The proposed framework was validated on 4 datasets from different domains, comprising both synthetic and real data.

3 PROPOSED APPROACH

Anomalies are data points or groups of data points that do not conform well to the whole dataset. Given a time series $X = \{x_1, x_2, \ldots, x_N\}$, it is possible to segment it in M subsequences as

$$X = \{S_1, S_2, \ldots, S_M\} \tag{1}$$

where each $S_i, i \in \{1, 2, \ldots, M\}$ is a subsequence of X composed of a defined number of data points, that may vary from segment to segment and each $x_t, t \in \{1, 2, \ldots, N\}$ is a measurement at instant t, where N is the total number of data points. Therefore, the time series may be represented as

$$X = \{\{x_1, \ldots, x_{k_1}\}, \ldots, \{x_{k_{M-1}+1}, \ldots, x_{k_M}\}\} \tag{2}$$

The analysis of each subsequence is usually accomplished using a cost function that may indicate distance or density, for instance. Thus, a subsequence S_i is anomalous if

$$f(S_i, S_j) > \delta \quad \forall j \in [1 : M] \tag{3}$$

where S_j may correspond to all subsequences except S_i, a model of a normal pattern, or a set of rules that S_i must obey to be considered a normal segment. The value of $f(S_i, S_j)$ is the anomaly score, which can be considered the *anomaly degree* of S_i and expresses the amount of dissimilarity to the model. The definition of the threshold, δ, controls the sensitivity of each algorithm.

The proposed approach, illustrated in Figure 1, starts with the application of an unsupervised segmentation algorithm used to extract each cycle from a repetitive time series. Then, each extracted cycle is represented by a set of features, followed by a process of dimensionality reduction using Principal Component Analysis. Finally, the transformed feature vector will be the input for a density based clustering algorithm - DBSCAN.

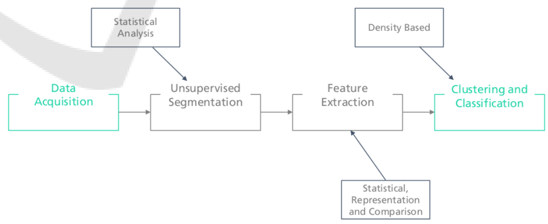

Figure 1: Diagram of the proposed approach.

3.1 Unsupervised Segmentation

In order to extract cycles from generic repetitive time series, it was developed a new unsupervised segmentation algorithm, capable of segment time series without prior knowledge about their morphology, period of repetition or number of cycles, hence, it is considered dictionary-free.

The developed algorithm is divided into two separate parts. The first part consists of iteratively segmenting a given time series in shorter portions, in a top-down fashion. Starting with k segments, in which its limits are constrained to be local minima in a specified range, the progression of the number of iterations results in an increase of the number of segments. Then, each segment is represented by its mean value, thus, each iteration is associated with the set of means of its segments. Each iteration is then represented by the standard deviation of the set of means.

The main assumption is that in an ideal cyclic signal, the mean of each cycle is identical to the rest, therefore, each value in the set of means is equal to the average value of the set of means, leading to a standard deviation of 0 ($\bar{S}_1 = \bar{S}_2 = ... = \bar{S}_M = \bar{S}_a \implies \sigma_a = 0$, where $\bar{S}_i$, $i \in \{1, ..., M\}$ are the mean values of each subsequence of a given iteration a, $\bar{S}_a$ is the mean value of the set of means of iteration a and σ_a is the standard deviation of the set of means of the corresponding iteration).

The second part of the developed algorithm is based on the function of standard deviation *vs* iteration. The iterations correspondent to local minima of that function, depicted in the right pane of Figure 2, are selected, as they correspond to the iterations in which the value of standard deviation decreases, which means that the segments are more similar.

With those iterations, it is computed the Pearson's Correlation Coefficient between each segment and the rest. Then, each segment is represented by the mean value of those coefficients and each iteration is represented by the mean of the representation of its cycles.

Hence, the value that represents each iteration is restricted to $[-1, 1]$. The selection of the correct segmentation is based on this value and corresponds to the iteration with the highest value, meaning that most segments are highly correlated to all others.

3.2 Feature Extraction and Dimensionality Reduction

In this work, a comprehensive range of statistical features, representation transforms and comparison metrics, was used and is summarised in Table 1.

While statistical features and representation transforms are applied for representing each subsequence, comparison metrics are used to compare each subsequence to the total number of subsequences of the time series. Anomalous subsequences will have a higher dissimilarity to normal instances, while the normal subsequences will have a high similarity to normal instances.

Following feature extraction, the set of features selected by the user are scaled using a z-score normalisation and then transformed by the computation of its Principal Components, and only the components with variance higher than 0,95 are kept for clustering and classification.

Table 1: Statistical features, representation transforms and comparison metrics used in this work.

Statistical Features	Representation Transforms	Comparison Metrics
- Mean Value - Standard Deviation - Minimum Value - Maximum Value - Inter-Quartile Range (IQR) - Number of Peaks - Median - Kurtosis - Skewness - Duration - Linear Regression (slope and y-intercept) - Zero Crossing Rate - Polarity - Cumulative Summation - Histogram	- Fourier Transform - Wavelet Transform - Principal Component Analysis Transform - Independent Component Analysis Transform - PAA in the Amplitude Domain (AD-PAA) (Ren et al., 2018) - PAPR (Ren et al., 2017) - Subsegment Analysis	- Euclidean Distance - Dynamic Time Warping Distance (DTW) - Time Alignment Measurement (TAM) (Folgado et al., 2018) - Pearson's Correlation Coefficient (PCC) - Cosine Similarity

3.3 Clustering and Classification

After feature extraction and dimensionality reduction, the resulting set of features is introduced as the input for an unsupervised clustering algorithm - DBSCAN (Ester et al., 1996).

In order to cluster data points, DBSCAN takes two hyper-parameters, ε and θ. Based in those parameters, there are three types of data points: core points, which are the points that have, at least, a number of θ data points within a range of ε; density-reachable points, which are points that belong to the neighbourhood of a core point, that is, are at a distance lower than ε to a core point, but do not have a number of θ data points within ε; noise, which are the points that do not have a number of θ data points within ε and are not density-reachable points.

DBSCAN is able to cluster data based on its density, but it does not classify each data point. The classification was performed based on the following considerations: given that the input to the algorithm are the features extracted and transformed from each segment representing the samples, if the number of segments considered to be anomalous is higher than the number of segments classified as normal, the value of ε increases by 10% and the clustering process is performed again. This process is repeated until the number of normal instances is higher than the number of anomalous instances. Furthermore, noise points are always regarded as anomalous and, in cases when there is more than one cluster, only the cluster with highest number of points is considered normal. This last consideration is important in cases in which anomalies may be similar, thus forming clusters of their own, such as arrhythmias in ECG signals.

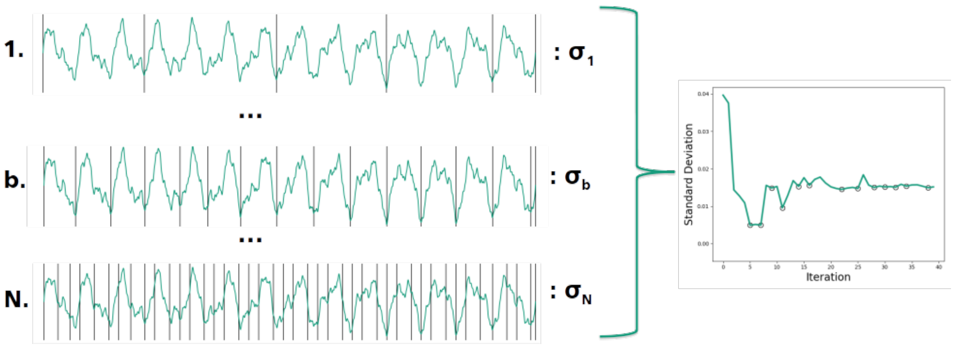

Figure 2: Top-down process of segmentation. Firstly, the time series is segmented in k parts. Then, with each iteration, the number of segments increases and in each iteration the mean of each segment is computed. Each iteration is represented by the standard deviation of the set of means of its segments forming a curve such as in the image in right. The negative inflexion points are chosen for the rest of the process. Iteration b corresponds to the correct segmentation and N corresponds to the last iteration.

4 RESULTS

The validation of the proposed framework was made with resource to four datasets, two synthetic and two composed of real-world data in order to demonstrate the potential of minimum effort application to different domains.

4.1 Numenta Anomaly Benchmark

The first dataset is composed of 9 artificial signals from Numenta Anomaly Benchmark (NAB) (Ahmad et al., 2017), illustrated in Figure 3, which was created to test an algorithm developed by Numenta, the Hierarchical Temporal Memory (HTM). Since the dataset comprises different types of anomalies, we only selected the ones which fulfilled the three assumptions made by the proposed framework.

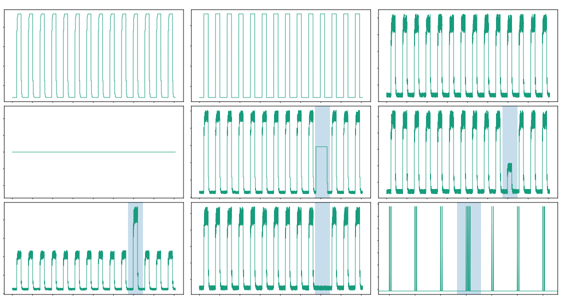

Figure 3: Numenta Anomaly Benchmark selected signals. The four initial signals do not present anomalies and, in the others, the existing anomalies are identified by blue shades.

The results obtained for this dataset are shown in Table 2.

These results were obtained using mean, maximum, minimum, median, inter-quartile range and skewness values as the input vector followed by the procedures described in Section 3. The choice of the parameters to use in DBSCAN was performed empirically by observing the results and tuning the parameters in order to optimise the achieved results. This is not ideal, because in real life scenarios it is impracticable to tune the parameters to new signals without prior knowledge about them. Nevertheless, the parameters are the same for all signals: $\theta = 5$; $\varepsilon = 5$.

Table 2: Results of anomaly detection using the Numenta Anomaly Benchmark.

Metric	Value (%)
Accuracy	99,3
Specificity	99,3
Sensitivity	100,0
Precision	83,3
F1 score	90,9

The results show an overfitting scenario due to the optimisation of the parameters that took into account all signals. Nevertheless, it is important to point out that the accuracy is not a good metric to assess the quality of classification in an unbalanced dataset, which contains a considerate higher number of normal segments than anomalous. For example, in the considered dataset, there are 147 segments and only 5 of them are anomalous. Thus, classifying all segments as normal, would give an accuracy of 96,6%, but the classifier would be useless for anomaly detection. Thus, the most appropriate metrics to study such scenarios are sensitivity, precision and F1 score. In this case, all metrics show high results except for precision, because there was 1 false positive, meaning that 5 positives were correctly classified among 6 detected positives.

4.2 Pseudo Periodic Synthetic Time Series

The Pseudo Periodic Synthetic Time Series dataset was made publicly available by the Center for Machine Learning and Intelligent Systems of the Bren School of Information and Computer Science of the University of California (Dheeru and Karra Taniskidou, 2017). It is composed of 10 artificial signals composed of 100.000 data points each. These signals are repetitive, but the cycles are not exactly alike.

These facts make this dataset suitable for testing the proposed framework, but there is a crucial aspect lacking to these signals, which is the presence of anomalies. Thus, it was generated a set of synthetic anomalies on amplitude (e.g. noise addition, multiplication by scale vector) and temporal (e.g. nonlinear temporal distortion) domains. Those anomalies were randomly introduced in the dataset in a controlled fashion. This procedure resulted in data augmentation from 10 to 500 signals, being able to generate a wide range of different anomaly types in different instants of the signal.

The results are presented in Table 3. In order to minimise the influence of overfitting, the hyper-parameter optimisation was only applied to a small percentage of data. Therefore, in the validation step, the majority of data being used was never been subject to the optimisation procedure. Although this procedure reduces metric performance, it is more appropriate and allows to understand the full extension of application in real scenarios. The best results were obtained using the details of the wavelet transform, in which the mother wavelet was chosen to be of the family of Daubechies of third order, using $\theta = 5$; $\varepsilon = 0,001$.

Table 3: Results (mean $\pm$ standard deviation) for pseudo-periodic signals dataset.

Metric	Value (%)
Accuracy	$91,6 \pm 5,8$
Specificity	$91,9 \pm 5,2$
Sensitivity	88 ± 28
Precision	52 ± 19
F1 score	64 ± 23

The results are lower than those obtained for NAB dataset. This is due to the fact that the anomalies are not as explicit as the ones in NAB and the fact that hyper-parameter tuning was performed on a small percentage of data. Specifically, the value of precision of 52% is low due to the fact that anomalies may be spread across segments, but could not occupy a whole segment. Thus, given that the classification was made in terms of segments, a segment containing an anomaly could have normal parts, which would be wrongly classified and are considered false positives, thus reducing the precision.

However, the results are more representative in terms of generalisation, which is an essential characteristic of machine learning applications.

4.3 MIT BIH Arrhythmia Database

MIT BIH arrhythmia database (Goldberger et al., 2000) is a dataset composed of real world ECG recordings acquired in ambulatory. Electrocardiography signals represent the measurement of the electrical pulse that propagates through the cardiac muscle in order to stimulate it, resulting on its normal behaviour, which enables the entry and exit of blood to and from the heart. This normal behaviour may be affected by various factors, resulting in the existence of cardiac arrhythmias.

The referred dataset is composed of both normal and anomalous heartbeats totalling 110.000 heartbeats. Each heartbeat was labelled by two specialist concerning the position of the R peak and its classification regarding the classification in various types of arrhythmia.

The R peak annotations were used to segment the signals in order to guarantee a correct segmentation. Therefore, a segment consisted of a portion of a signal from the R peak less 100 data points until the next R peak minus 100 points.

Moreover, it was applied a Butterworth band-pass filter of second order in order to attenuate frequencies lower than 1 Hz and higher than 20 Hz, enabling to reduce interference from normal respiratory frequencies, and muscular and digital noise, respectively.

The results are presented in Table 4. The best features were duration, polarity, linear regression and maximum value of each heartbeat. Unlike the first two datasets, and because the number of heartbeats (cycles) per signal is significantly higher than in the previous datasets, it was possible to use the k-Nearest Neighbour (k-NN) curve to estimate ε, used by the DBSCAN algorithm, automatically for each signal, given a fixed θ. Thus, using $\theta = 5$, ε was specific for each signal.

The performance metrics reveal that real world electrophysiological signals have considerably more complex structures and in which anomalies may occur in several forms. These results are representative about the accuracy score, which is high, but F1-score is low. This means that, the great majority of the dataset is correctly classified, but that is because

Table 4: Results (mean $\pm$ standard deviation) for anomaly detection for the MIT BIH arrhythmia database.

Metric	Value (%)
Accuracy	89 ± 12
Specificity	92 ± 10
Sensitivity	82 ± 30
Precision	41 ± 33
F1 score	44 ± 33

most normal cycles are considered normal, but several anomalous cycles are wrongly classified, which lowers the value of sensitivity. However, it is notable the low adaptation effort needed to apply the developed generic framework to such a specific domain such as ECG signals.

4.4 Human Motion on Industrial Scenario

Human motion on industrial scenario (HMIS) dataset was acquired by the authors in a real industrial environment with resource to a wearable sensor, that was integrated into bracelets and placed on employees' dominant upper member. This placement allowed to monitor the wrist's movement performed by each monitored employee, which is relevant once the tasks performed involve predominantly upper member movements.

The sensing device contains an Inertial Measurement Unit (IMU), which measures inertial data with resource to three sensors: an accelerometer, a gyroscope and a magnetometer. The combination of the three sensors allows a full comprehensive analysis regarding the movement of the monitored employee. Figure 4 shows an example of the measured inertial data from a single employee. The black vertical lines indicate the beginning/ending of a work cycle and the red part is an example of an anomaly in this context, which corresponds to a significant deviation in terms of morphology in relation to other cycles (the phenomenon is more evident in magnetometer data).

The device was connected via Bluetooth LE to a smartphone, where the data was stored. Each recorded acquisition was annotated in real-time at the beginning of each new cycle and in every occurrence of anomalies, allowing to build the ground-truth segmentation and labelling.

The acquired data consists of inertial data originated by the movements performed by 4 different workers at 3 different workstations where they were producing different items. All tasks monitored were repetitive which made them suitable to be tested with the developed anomaly detection framework. The sampling frequency of the acquisitions was approximately 100Hz and the total time of the acquisitions is around 4 hours and 20 minutes.

Moreover, once the number of cycles per signal varies widely, it was not possible to use the k-NN curve directly in order to estimate them. The followed approach was inspired by the Leave-One-Out cross validation that is used to test algorithms in the presence of a low number of instances. Given N signals, we calculate the parameters for every signal, except the signal under evaluation, with resource to the k-NN curve and then use the mean value of the estimated values for the untested signal. This process was repeated for each signal allowing for an objective test without influence from a human observer.

Table 5 summarises the results of anomaly detection using two different methods for time series segmentation in work cycles: groundtruth annotations and the proposed unsupervised segmentation algorithm. The results suggest that both methods have similar performance. The use of the unsupervised segmentation does have significant advantages on real-world deployment as it does not require user intervention in the overall process.

Table 5: Influence of unsupervised segmentation on anomaly detection of human motion inertial data. The results (mean $\pm$ standard deviation) are reported in terms of percentage (%).

Metrics	Groundtruth Segmentation	Unsupervised Segmentation
Accuracy	73 ± 19	71 ± 16
Specificity	75 ± 22	74 ± 18
Sensitivity	52 ± 45	52 ± 36
Precision	18 ± 23	20 ± 24
F1 score	19 ± 25	20 ± 20

Since previous results suggest that it is feasible to use the unsupervised segmentation algorithm, the next step consisted of a comprehensive evaluation of the features used to describe the detected subsequences and thus, able to differentiate between normal and anomalous instances. Table 6 presents the results obtained using each feature earlier described in Table 1. The results show that feature selection influences the outcome of the clustering algorithm.

The achieved results have overall low performance in comparison with previous datasets due to some factors that will be properly discussed. Firstly, the process for hyper-parameter optimisation of DBSCAN algorithm was different from previous datasets. In the NAB and Pseudo Periodic datasets the hyper-parameters were specified and optimised by the user; in the MIT BIH arrythmia database they were

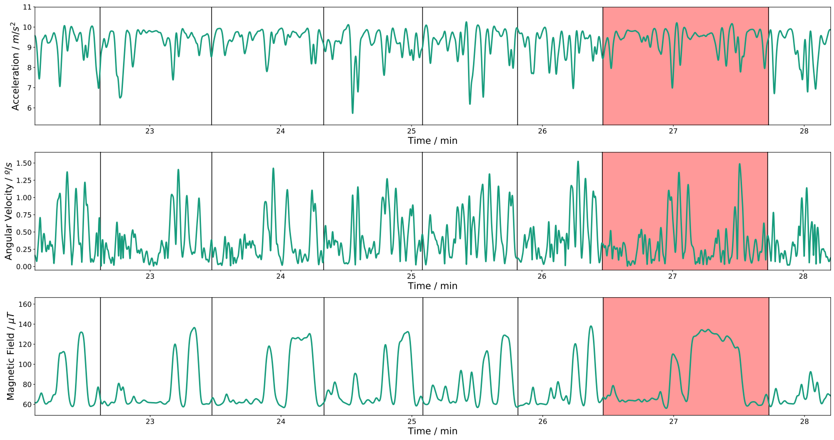

Figure 4: Excerpt of inertial data from a single operator. Each sensor is represented by the magnitude of the three axis x, y and z ($magnitude = \sqrt{x^2 + y^2 + z^2}$). Each plot corresponds to accelerometer, gyroscope and magnetometer data, respectively, from top to bottom. The black vertical lines indicate the beginning/ending of a work cycle and the red part corresponds to an anomaly. The anomaly is more evident in magnetometer data.

Table 6: Influence of feature selection on anomaly detection of human motion inertial data. The results (mean $\pm$ standard deviation) are reported in terms of percentage (%). (In the first line, the set of features correspond to the mean, maximum, minimum, IQR, standard deviation, number of peaks, median, kurtosis, duration, skewness and linear regression).

Features	Accuracy	Specificity	Sensitivity	Precision	F1-score
Set of Features	73 ± 19	74 ± 21	74 ± 35	24 ± 30	30 ± 31
ICA	89 ± 13	96 ± 11	9 ± 28	23 ± 24	6 ± 17
DTW	72 ± 18	77 ± 21	53 ± 44	15 ± 13	17 ± 18
TAM	70 ± 19	70 ± 22	72 ± 41	17 ± 24	23 ± 28
Fourier Transform	74 ± 16	80 ± 19	28 ± 34	14 ± 22	13 ± 17
Polarity	70 ± 17	77 ± 21	38 ± 48	$5,3 \pm 9,3$	8 ± 14
Cumulative Summation	75 ± 20	80 ± 24	28 ± 45	7 ± 12	7 ± 15
Wavelet Approximation	80 ± 23	82 ± 28	40 ± 52	20 ± 26	15 ± 27
Wavelet Details	65 ± 18	64 ± 22	67 ± 47	14 ± 17	20 ± 23
Cosine Similarity	77 ± 21	78 ± 24	53 ± 47	25 ± 24	22 ± 28
PCA	75 ± 20	75 ± 25	53 ± 48	20 ± 17	19 ± 23
AD-PAA	74 ± 18	75 ± 20	59 ± 47	23 ± 29	29 ± 33
Histogram	65 ± 20	65 ± 21	74 ± 32	25 ± 30	30 ± 31
Euclidean Distance	73 ± 22	71 ± 27	58 ± 50	21 ± 17	20 ± 24
Subsegment analysis	67 ± 20	66 ± 21	79 ± 32	18 ± 24	25 ± 28
PCC	69 ± 18	76 ± 23	42 ± 47	9 ± 15	$6,6 \pm 7,3$
PAPR	74 ± 18	76 ± 20	64 ± 40	25 ± 33	29 ± 33

directly estimated with resource to the k-NN curve. For the HMIS dataset the parameters were selected by a Leave-One-Out approach, since the reduced number of cycles per signal did not allowed to use the k-NN curve method directly. Secondly, the motion data was originated from three different workstation which have different methods and thus, different cyclic behaviours and signal morphologies. Therefore, the mean value of the estimated parameters from different workstations may not represent the correct value for neither of them. The most adequate approach would be to acquire data for a longer period of time in order to have a dataset composed of longer time series with a higher number of cycles, which would allow to automatically estimate the value of parameter ε for each workstation.

5 CONCLUSIONS

Musculoskeletal disorders are a major concern in manufacturing environments due to wrongly executed movements and inadequate postures. Most of the tasks executed in those environments are repetitive. Using IMUs to follow human motion, it is possible to acquire repetitive time series with all the information regarding the movements that integrate each task. Since the method to accomplish each task is defined with the aim to increase productivity while preventing the development of musculoskeletal disorders, any significant deviation from it may suggest an occurrence that hinders the productive process. Those occurrences appear as anomalies on IMU data. This high-level information is a valuable asset for production control systems, being able to constantly identify opportunities for continuous refinement of the production processes in lean manufacturing environments.

In order to accomplish this requirement, the proposed anomaly detection framework was divided into three stages: (1) unsupervised segmentation; (2) feature extraction from the extracted subsegments and (3) unsupervised classification using DBSCAN.

The validation stage comprised the performance evaluation on four datasets from different domains, which proves the requirements were met with regards of aspiring to build a framework for unsupervised anomaly detection on repetitive time series.

The results demonstrated that anomaly detection in generic repetitive time series in an unsupervised fashion is feasible, however, at the cost of a reduced performance when compared to domain-specific approaches reviewed in the literature. Notwithstanding, a general approach has the value of being easily adapted in order to be applied in different domains and in repetitive time series with different morphologies, such as the case of different workstations in manufacture environments. In human motion industrial scenarios, which are dominated by repetitive movements, it was possible to detect anomalies in multivariate time series using accelerometer, gyroscope and magnetometer data. However, the detection depends on the correct feature selection in order to be accurate and still it may present low precision. Another important aspect is the adequate selection of DBSCAN hyper-parameters. This work demonstrated that a high volume of data and cycles are required in order to properly automate the hyper-parameter selection. For challenges with relatively low volume of data either the hyper-parameter optimisation was achieved by user selection (at the cost of low generalisation properties despite high performance values) or by a Leave-One-Out methodology which resulted in difficulties to achieve a set of values which maintain optimal characteristics for a wide range of signals.

Future work will consist in validating the framework over a more exhaustive volume of data, which should facilitate the process of proper hyper-parameter optimisation. Furthermore, this work was focused on the development of the described anomaly detection framework, but it would be important to assess the impact of this system in Industrial production lines in long-term.

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