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Interactive data visualization of chatter conditions in a cold rolling mill

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ABSTRACT

Rolling of flat steel products is an industrial process in the field of metalworking where two or more pairs of rolls reduce the thickness of a steel strip to produce a uniform thickness material. Despite it has been studied for many years, there are still unpredictable problems that can affect the final quality of the product. One of them is the so-called *chatter*, that is a powerful self-excited vibration that appears suddenly and limits the productivity of the process. In this paper, a visual analytics approach is considered for exploratory analysis in order to discover and understand the factors and conditions under which chatter appears. An interactive web-based interface is presented here which allows the user to explore a map of dynamical conditions and visualize relevant details of each chatter onset. A validation case is performed using real data where normal/fault conditions have been identified automatically. By means of interactive exploration, the tool allows to refine an automatic chatter detection method. Moreover, it is shown to reveal correlations between variables, providing in some expected cases data-based confirmation, but also revealing less obvious relationships. Finally, it provides context, allowing to carry out comparative analysis, both qualitative and quantitative, for different subsets of coils (e.g. different years) as well as for different working conditions.

1. Introduction

The rolling process transforms the shape of a steel material by means of a thickness reduction passing it between two or more pairs of rolls held by a mill stand. This process is different depending on the temperature of the rolled material. Precisely, a cold rolling mill [21] produces smoother finished products with a uniform exit thickness, commonly performed continuously through several stands in tandem mills. Despite it is an universal process in metalworking, there are still problems that cause economic losses in modern rolling mills. Moreover, the conditions under which these problems arise are not completely understood, making it difficult to prevent their occurrence.

One of the main problems is a self-excited vibration mode called *chatter*, that appears in rolling operations, provoking unacceptable gauge variations in the final surface of the strip, as it is explained in [26]. The removal of chatter is performed by means of a decrease in the rolling velocity. This involves a loss of productivity which makes chatter not only an industrial concern but also an economic one. The analysis of chatter requires understanding the conditions that lead to the instability of the process. The dynamic interactions between structural phenomena in the mill and the rolling process have been studied along years using theoretical models [18,1,30,19,31]. However, these models may be too complex with a large amount of parameters to be applied easily or have so many assumptions that excessively simplify the real problem. Tuning these models to suit a particular facility can be very costly requiring the availability of process data and calibration/optimization methods to estimate the model's parameters. On the other hand, rolling mills involve a large amount of interactions featuring coupled thermal, mechanical and computer systems for control. Besides being complex, their dynamics are constantly evolving as a result of changes in the mechanical properties of rolling elements, misadjustments, changes in the working point, etc. Also, the same model needs to be retuned if applied to other mill, even if it is of the same characteristics. All this poses the need for data-based approaches, that are based on the actual behavior of the process.

The current technologies facilitate data acquisition of many parts of a process, described by a large number of variables, and their massive storage in databases is a very common procedure. *Intelligent data analysis* (IDA) algorithms extract information automatically in order to discover new knowledge that may have stayed hidden. A proper visual presentation of the results from these algorithms is an excellent way for communication [27] and efficient interpretation which supports the decision. The so-called

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visual analytics (VA) methods exploit the combination of automatic computations with visualization techniques to support analytical reasoning through interactive interfaces [25,13]. In this way, the use of data visualization, machine learning and agile user-interaction mechanisms makes the analysis be supported by user's expert knowledge and empower intuition, while providing at the same time with solid quantitative information based on computations on the actual data.

In this paper, an approach to chatter analysis using the VA paradigm is proposed, allowing the user to explore the dynamical conditions of the process. This is done through an interactive web-based prototype, where automatic algorithms extract dynamic behaviors of normal operation and chatter fault from real data. These dynamic behaviors, characterized by high-dimensional feature vectors, are represented on an interactive interface where the user can explore them and get details on demand. This is performed by means of several views showing a spectrogram display, a 2D map of dynamic conditions and barcharts, including interactive mechanisms which provide coordinated links between all these views. The paper is organized as follows: in Section 2 previous works of analysis of the process and related data analysis methods are reviewed; in Section 3 data analysis methods for dealing with chatter fault are proposed; in Section 4 a real validation case is described and a web application design is presented; finally, Section 5 concludes the paper and suggests directions for future work.

2. Related work

Vibration phenomena appear in rolling processes as a result of dynamic interactions [26] between the mill stand structure and the strip material. There are two main different vertical vibration modes, third-octave-mode chatter (120–250 Hz) and fifth-octave-mode chatter (500–700 Hz), being the former one more harmful, that occurs suddenly, accumulating a large quantity of energy within a few seconds, so that chatter is referred here as this third-octave-mode vibration. Several works have studied this phenomenon along many years, the earliest studies are [30,19], or [24] that define chatter as self-excited vibration and they study possible causes through models.

In [31] several models for the structure of the mill and the rolling process are reviewed and then combined to obtain chatter models. For the case of the structural model, the classical ones are based on the mass-spring system, where forces are represented in terms of stiffness and damping. Since some of these models assume symmetry with respect to the roll gap, only the top part of the mill is considered in the analysis.

The models for the rolling process are mathematical expressions related to rolling parameters that help in determining, for example, roll force, torque, neutral point, strain, etc. They involve coefficients such as yield stress and friction, which can vary during the process [18,1].

Later, more works were made considering not only a static analysis but also a dynamic one in order to obtain a better understanding of the problem [10,11]. In [29] a single-stand chatter model in state-space is proposed coupling models for the dynamic rolling process, the stand structure and the hydraulic servo system and it is simplified to perform a robust thickness control. A multiple-modal-coupling dynamic model is proposed in [32] to characterize the coupling relationship between mill structure and the rolling process. The optimization of rolling parameters and their influence on the system stability are studied in [6]. Also the use of multistand models in tandem mills explained in [12] increases the complexity of the study. However, there still remain issues to fully understand the conditions which lead the system to this instability.

Recently, more models related to chatter have been proposed. For instance, a rolling force fluctuation model is proposed in [28] to identify chatter marks. Furthermore, time delay effect in tandem mills is analysed in [15] showing its influence in the change of the optimal parameters. Besides, wave propagation theory is studied in [17]. Simulation and experimental data of two stand rolling mill are compared and predicted values for chatter frequency and critical speed present low error values. Other models introduce friction, which is an important factor in mill vibration. Examples include a numerical model based on friction models in [8] where it is shown that friction coefficients of a two stand rolling mill are dependent, or models based on unsteady lubrication whose results show a direct correlation between critical rolling speed and limiting shear stress in [7], and the replication of chatter conditions in [9]. Many existing chatter models are valuable in providing insight into the problem. Also, they can be very effective, provided a proper parameter adjustment is done.

Data analysis algorithms extract information that can be used to understand and support decisions. A particularly well-known approach in this field are *dimensionality reduction* (DR) techniques. These methods allow to project high-dimensional data points on a low-dimensional latent space – typically 2D or 3D –, which can be visualized. A detailed revision of these techniques can be found in the book of [14]. Some of these data-based methods were applied to study dynamical conditions in real scenarios previously. For

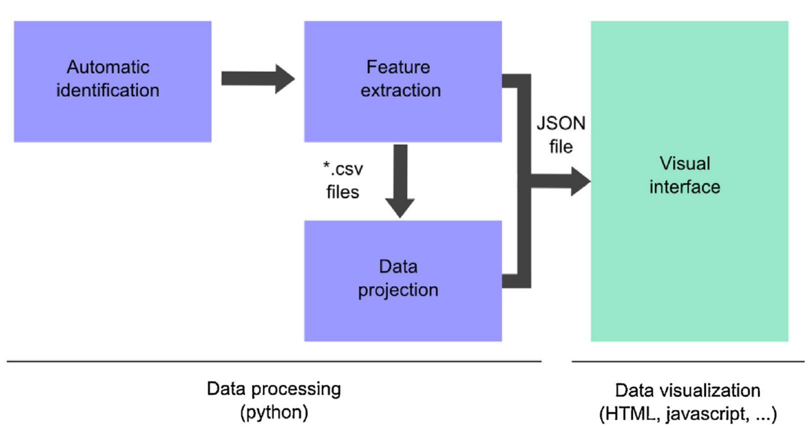

Fig. 1. Scheme for the method where dynamic features are projected on a visualization space for data exploration.

example, self-organizing maps (SOM) have been used for exploring dynamics of industrial processes such as steel rolling mill behavior [3]. Maps of vibration states from a rotating machine were obtained using DR techniques in [2] where a comparison is done showing the results obtained by manifold learning approaches. Also a frequency band analysis of a cold rolling mill is shown in [20] where dynamical behaviors of the process are projected into a static view.

Although these works provide maps for analyzing dynamical behaviors in a visual manner, with certain advantages in providing insight from data, there is a lack of interaction that can greatly improve data exploration. Interaction is a key part in visual interfaces because it enables user-driven manipulation of the representation. An interesting approach is the consideration of data cubes [5] and their operations for multiway data analysis. An interactive application based on coordinated barcharts was proposed in [4] where attribute filtering, aggregation functions and real time visualizations were used for an energy analysis of public buildings. This approach provides on-line analytic processing, resulting in an effective human-in-the-loop analysis for finding relational factors.

This type of interactive data exploration can help to give insights in complex problems such as chatter in a cold rolling mill where there are still open issues to understand the problem.

3. Methods

The methods of the proposed approach can be divided in two main parts: data processing, which includes automatic algorithms used for intelligent data analysis, and data visualization where results can be explored using an interactive visual interface. A general scheme of the proposed approach, composed of several stages, can be seen in Fig. 1.

3.1. Data processing

In this section the details of a procedure for chatter data analysis are described in order to provide intuition about the problem. First, an automatic identification of dynamic behaviors is performed for normal and chatter conditions; then a feature extraction and several machine learning techniques are applied on these conditions in order to obtain a 2D projection. These methods are detailed below.

3.1.1. Automatic identification of conditions

Using domain knowledge about the conditions under which the rolling mill is working normally and those under which it operates in the presence of chatter phenomena, we can design methods to identify these working operations automatically, as we show next.

Chatter conditions. Chatter episodes can be detected by analyzing either the deviation of the output thickness or the vibration in the 5th stand. Also, this detection is confirmed by the identification of a decrease in the rolling velocity $v(t)$ that the detection system currently installed performs in the rolling mill to mitigate the chatter. In Fig. 2a, a scheme for the chatter identification method is shown, which can be divided into the following steps:

- The spectrogram of the exit thickness deviation signal is computed within the frequency band where chatter appears (120–180 Hz). The maximum value of the amplitude $A(t)$ of the spectrogram in this frequency band is tracked.
- A logic signal is set to 1 while $A(t)$ exceeds a threshold value A_c of 0.01%. The time d during which $A(t)$ remains above this threshold is computed using edge detection on the logical signal.
- The initial and final moments (t_1 and t_2, respectively) that define the decrease in the rolling velocity are found using standard deviation on windows of the velocity signal as a measure to detect changes in it; the mean velocities v_1 and v_2 are computed at t_1 and t_2.
- The relative variation in velocity during the decrease is computed as:

$$\Delta v_r = \left(\left| \frac{v_2 - v_1}{v_1} \right| \right) \times 100(\%).$$

If it is less than a minimum of 4% then the chatter episode will be discarded.
- Two new times $t'_1 = t_1 - t_{margin}$ and $t'_2 = t_2 + t_{margin}$, are defined, being $t_{margin} = 0.25$ s.

In Table 1 several values, that were used in the experiments for the parameters of the method are detailed.

Normal operation conditions. The identification of normal working conditions in the produced coils is implemented by detecting constant intervals of rolling velocity in the last stand, and

Table 1
Parameters used for automatic chatter identification.

Parameter	Value
Chatter frequency band	120–180 Hz
Main threshold for detection (A_c)	0.01%
Minimum velocity variation (Δv_{rmin})	4%
Temporal margin (t_{margin})	0.25 s

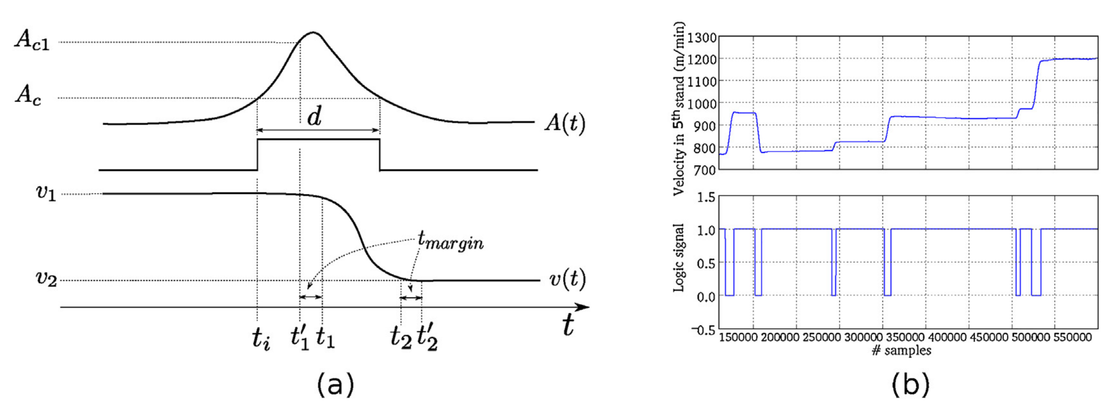

Fig. 2. Scheme for automatic identification (a) maximum amplitude harmonic $A(t)$ and rolling velocity $v(t)$ in chatter condition (b) rolling velocity signal of the last stand and logical signal detecting normal condition.

discarding its variations such as the beginning or end of the rolling process.

Constant velocity intervals are considered by computing the difference in rolling velocity between two consecutive samples, and then setting a logic signal to 1 if this difference signal is below a specific threshold of 2×10^{-3} m/min, fixed empirically. In Fig. 2b (top) the rolling velocity signal of the last stand is shown during part of the production of one coil. Below, the logical signal created to define the corresponding constant intervals of this signal is represented. Edge detection of this logical signal provides the starting and ending points for normal operation conditions. A minimum duration of 5 s is taken for the constant velocity intervals in order to be considered normal operating condition.

3.1.2. Feature extraction.

Once both kinds of conditions are detected, segments of 1-s duration are taken in order to extract a set of features describing the corresponding dynamical condition. Thus, constant rolling velocity intervals (normal operation conditions) are divided into parts of 1 s. For the case of chatter, a single 1-s segment can be taken just before t'_1 (see Fig. 2a), that is, in the interval $[t'_1 - 1, t'_1]$; alternatively, several consecutive 1-s segments can be taken *before* t'_1 and symmetrically, the same number of segments *after* t'_2. Here, we have considered both scenarios to collect a wide range of analysis data near the fault. The number of seconds considered near the fault are labeled in a new variable called *labelTimeChatter*.

The extraction of the features, in this case, consists in the computation of parameters such as the mean or the standard deviation (*std*) of several variables. These variables are detailed in Table 2.

Parameter α. In the case of a chatter condition, also a coefficient α is computed by fitting the tracked maximum harmonic $A(t)$ to an exponential growth curve, that is $A(t) \approx Ke^{\alpha t}$, using least squares.

Table 2
Description of features.

Feature	Units
Identification number of coil	–
Type of material	–
Target entry thickness	μm
Target exit thickness	μm
Width of the coil	mm
Rolling force in 4th stand (mean)	t
Rolling force in 5th stand (mean)	t
Tension between 3–4 stands (mean)	t
Tension between 4–5 stands (mean)	t
Rolling velocity 3th stand (mean)	m/min
Rolling velocity 4th stand (mean)	m/min
Rolling velocity 5th stand (mean)	m/min
Vibration 4th stand (std)	g
Vibration 5th stand (std)	g
Exit thickness deviation 5th stand (mean, std and rms)	%
Reduction $\left(1 - \frac{v_{entry}}{v_{exit}}\right)$ 4th stand (mean and std)	–
Reduction $\left(1 - \frac{v_{entry}}{v_{exit}}\right)$ 5th stand (mean and std)	–
Roll bending force 4th stand (mean)	t
Roll bending force 5th stand (mean)	t
Forward slip 4th stand (mean)	%
Forward slip 5th stand (mean)	%
Direct application (DA) emulsion concentration (mean)	%
Refrigeration central zone 4th stand (mean)	%
Refrigeration central zone 5th stand (mean)	%
Refrigeration lateral zone 4th stand (mean)	%
Temperature of strip between 3–4 stands (mean)	°C
Temperature of strip between 4–5 stands (mean)	°C
Temperature of strip (mean)	°C
Temperature of water (mean)	°C
Temperature of DA emulsion (mean)	°C

Table 3
Description of variables used in the projection.

Variable	Units
Vibration in 4th stand(std)	g
Vibration in 5th stand (std)	g
Rolling force in 4th stand (mean)	t
Rolling force in 5th stand (mean)	t
Tension between 3–4 stands (mean)	t
Tension between 4–5 stands (mean)	t
Rolling velocity 3th stand (mean)	m/min
Rolling velocity 4th stand (mean)	m/min
Rolling velocity 5th stand (mean)	m/min
Exit thickness deviation 5th stand (rms)	%

This parameter can be used as an estimation of the severity of the instability produced by the fault.

3.1.3. Data projection

A dimensionality reduction for 2D projection of the rolling states was done on a subset of the features from Table 2, that are listed in Table 3. To obtain a manageable dataset for projection, a method summarized in the block diagram of Fig. 3 is carried out. Since there is a large quantity of normal conditions (more than one million of samples) that can be identified, a subsampling operation, followed by a vector quantization stage using the k-means algorithm are applied to reduce the data size for this type of condition. The resulting centroids are representative prototypes of the normal conditions of the process, but they are not actual process data points. In order to work using real dynamic situations, the normal conditions points closest to the resulting centroids were considered. Gathering all the feature vectors for both chatter and normal conditions, a data matrix is built and then normalized by removing the mean and scaling to unit variance for each variable.

A 2D projection of the feature vectors is obtained for visualizing similarities using the t-SNE dimensionality reduction technique [16], that outperforms the former ones based on basic distance preservation schemes in terms of visualization.

In addition to this, a novelty detection algorithm is used to obtain decision boundaries that provide a visual delimitation of the normal working operations from the abnormal ones (e.g. chatter states) in the 2D projection view of the visual interface. To achieve this, a one-class support vector machine (SVM) classifier [22] is trained using normal states, allowing to predict for a test feature vector whether it is a normal state or a different one which is considered anomaly. The value of the decision function is obtained for all the points of a regular 2D grid in the projection view by computing the trained SVM model on high-dimensional feature vectors obtained by mapping back the 2D grid points on the feature space using a general regression neural network [23]. The resulting contour lines are visualized as decision boundaries of normal working operation in the projection space.

3.2. Data visualization

A web-based interface was developed in order to provide a framework where the information can be easily explored through an interactive data visualization. The system can perform an effective data exploration for a large number of variables and normal/fault states by loading, in the application, a previously computed data file. The design of the application includes a scatterplot visualization to represent the data projection, a spectrogram view of the fault states, descriptive tables and interactive barcharts for all available variables. In Fig. 4 a screenshot of the application that includes all the views mentioned is shown.

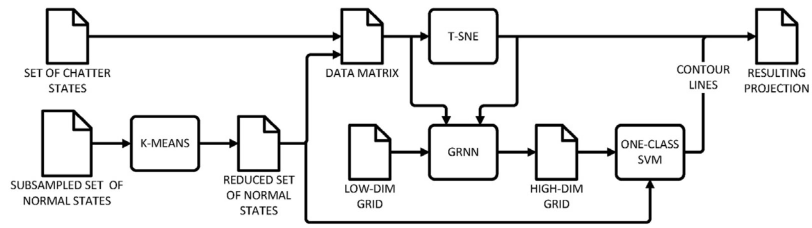

Fig. 3. Flowchart for obtaining data projection.

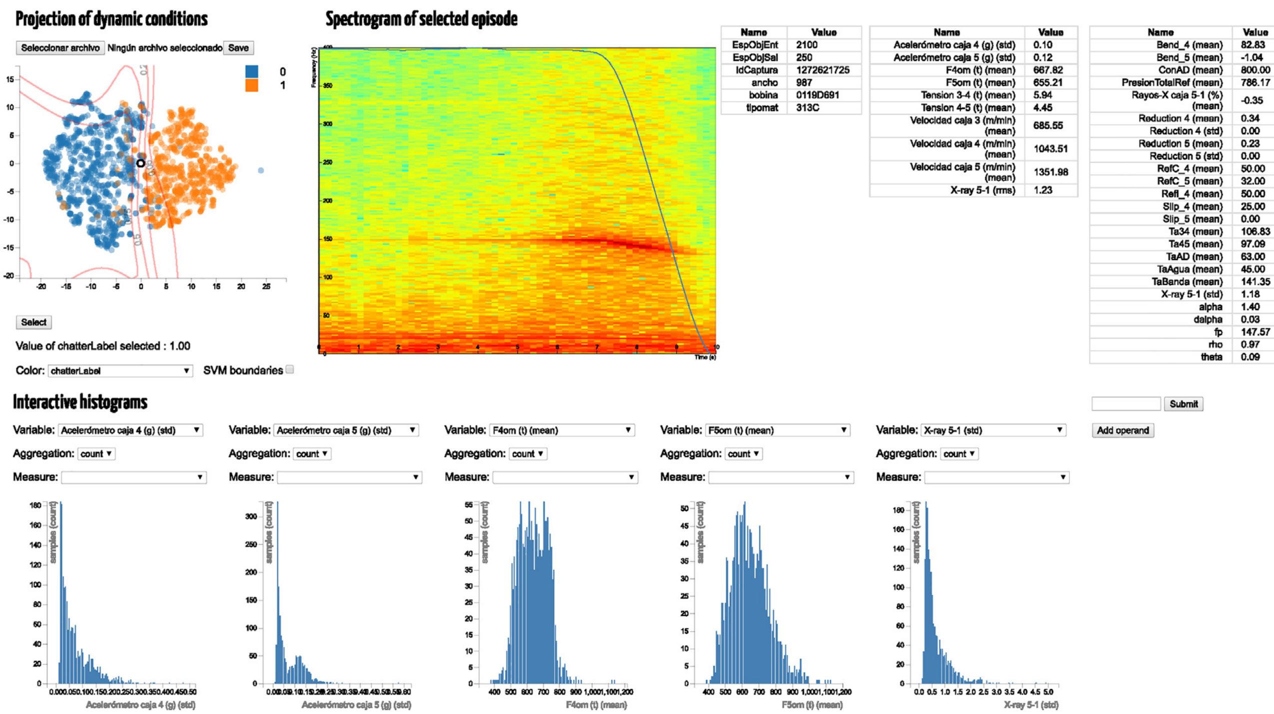

Fig. 4. Screenshot of the application developed.

The scatterplot visualization, that shows the data projection resulting from a DR technique (in this case the *t*-SNE), provides a 2D map (of two latent variables) in which close points represent similar states. This allows the user to explore different working points of the process on a general view quickly. Moreover, the color of the points represents the value of one variable, that can be selected by the user, and this value is displayed below, after mouse over. Also, the user can check the decision boundaries computed from the SVM model for several training errors, by means of contour lines visualized over the points. The user can select any parts of the projection and perform other interaction mechanisms such as zoom or pan, that help in the exploration.

The evaluation of chatter states can be efficiently performed through the spectrogram visualization, which provides a detailed time-frequency representation of the fault. This view (see Fig. 4) is shown by moving the mouse over the points of chatter states. The blue line over the spectrogram indicates the relative variation in the rolling velocity of the last stand of the mill which can be seen as a reference stand. Also interaction mechanisms, such as zoom, pan on the spectrogram, give the user more control to get further details of each episode. These details are displayed in tabular forms next to the spectrogram, so that the table on the left contains metadata such as the width or the identification number of the coil; the table in the middle contains the values for the variables used for computing the projection; and the table on the right contains the rest of the variables.

In order to perform an exploration that includes all the variables, a multiway analysis is allowed using interactive datacubes, presented in form of coordinated barcharts [4]. Using these charts, an advanced exploration can be performed through user-driven attribute filtering, aggregation functions and a real-time update of the results.

In practice, a datacube can be seen as a representation of a multidimensional data table whose records (rows) are composed of measures (values) of a set of fields (columns) or dimensions. Fields can be grouped in different ways – by class values, by intervals or bins, etc. – resulting in different types of attributes. A typical representation is the *histogram*, where a dimension is grouped into bins and the number of elements on each bin are represented by means of bars of proportional lengths. In the application, five configurable charts are included (see the bottom of Fig. 4) allowing to represent five different attributes at the same time. The user can choose any variable of the dataset to be represented in any chart. In addition to this, the user can create an extra barchart representing user-configurable mathematical operations between different variables. By default, the aggregation function for a barchart is the *count* operation, thereby resulting in a histogram, but other types of aggregations can be used. In the application, *sum* and *average* aggregations can be applied to measures of any attribute that the user wants to analyze. The configuration of the chosen variable, the type of aggregation and the computed measures are performed by means of combo boxes

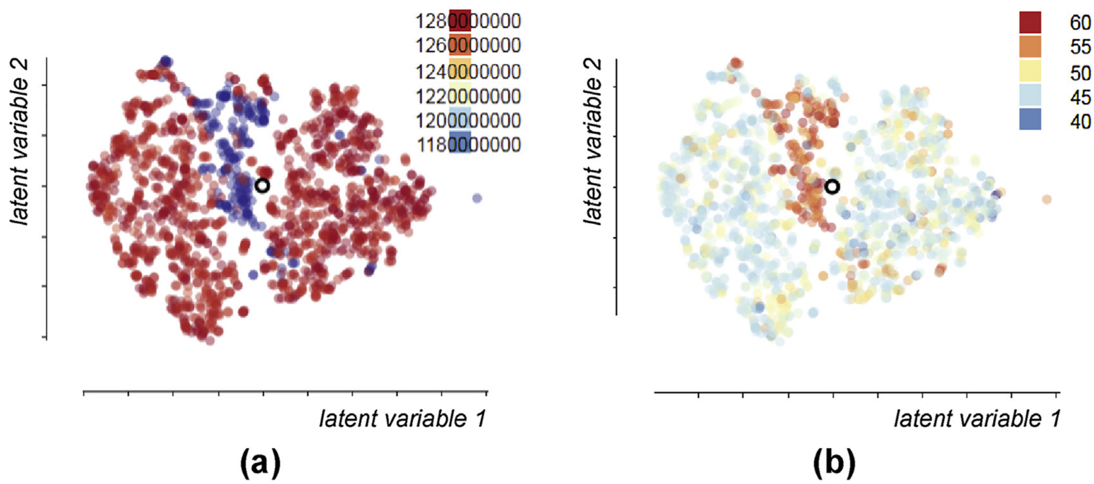

Fig. 5. Data projection with color representing: (a) Identification number of coil related to date and (b) temperature of water.

on each barchart. When the user defines a filter in any attribute, the rest of views recompute all their values accordingly for their corresponding configurations. Hence, the information presented using coordinated barcharts allows the user to find patterns and correlations easily.

Finally, the application establishes connections not only among barcharts but also with the scatterplot visualization, so that any filter applied by the user in any view, updates the rest of visualizations.

4. Use case

4.1. Real data analysis

Real data from a tandem mill of a cold rolling process, including the production of 4102 coils, were used to validate the analysis. The algorithms described in Section 3 were developed in Python and the web interface was implemented in Javascript, including specific libraries such as D3.js or crossfilter.js. The variables selected to perform the dimensionality reduction were chosen empirically and they are described in Table 3. The features extracted from the considered segment of the signal (1 s) are indicated in the table in parenthesis. The instants for the chatter condition in the projection were considered under two scenarios (depending on the file the user loads in the application): in the first scenario, this condition corresponds to 1 s previous to the automatic identification, as it was explained previously; in the other scenario, the user can analyze the evolution of the fault for a wider timespan. In this case, 5 previous seconds and 5 following seconds were considered for analysis.

The method explained in Section 3.1.3 is applied to a training set of the normal conditions with a size of more than 1 million observations. The subsampling operation reduces the set to 10000 samples and the *k*-means algorithm results in 1000 centroids, whose nearest points are computed.

The number of identified chatter conditions will depend on the configuration of the parameters of the automatic algorithm of detection (see Table 1 for details). For example, an initial computation had 722 chatter faults identified, but if there are some changes in any parameter, this number of detected faults will

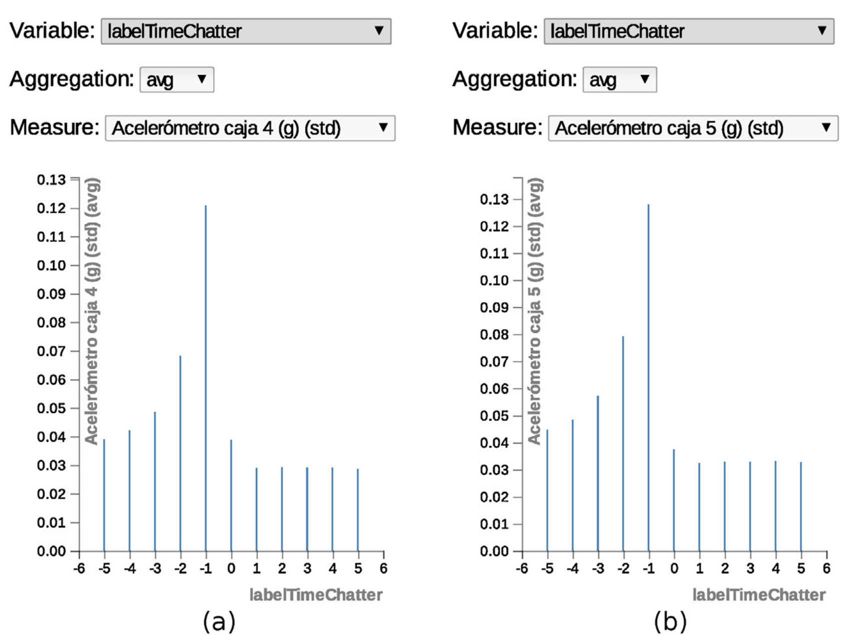

Fig. 6. Barcharts of average standard deviation of vibrations: (a) in 4th stand and (b) 5th stand in an interval of 10 s during the fault.

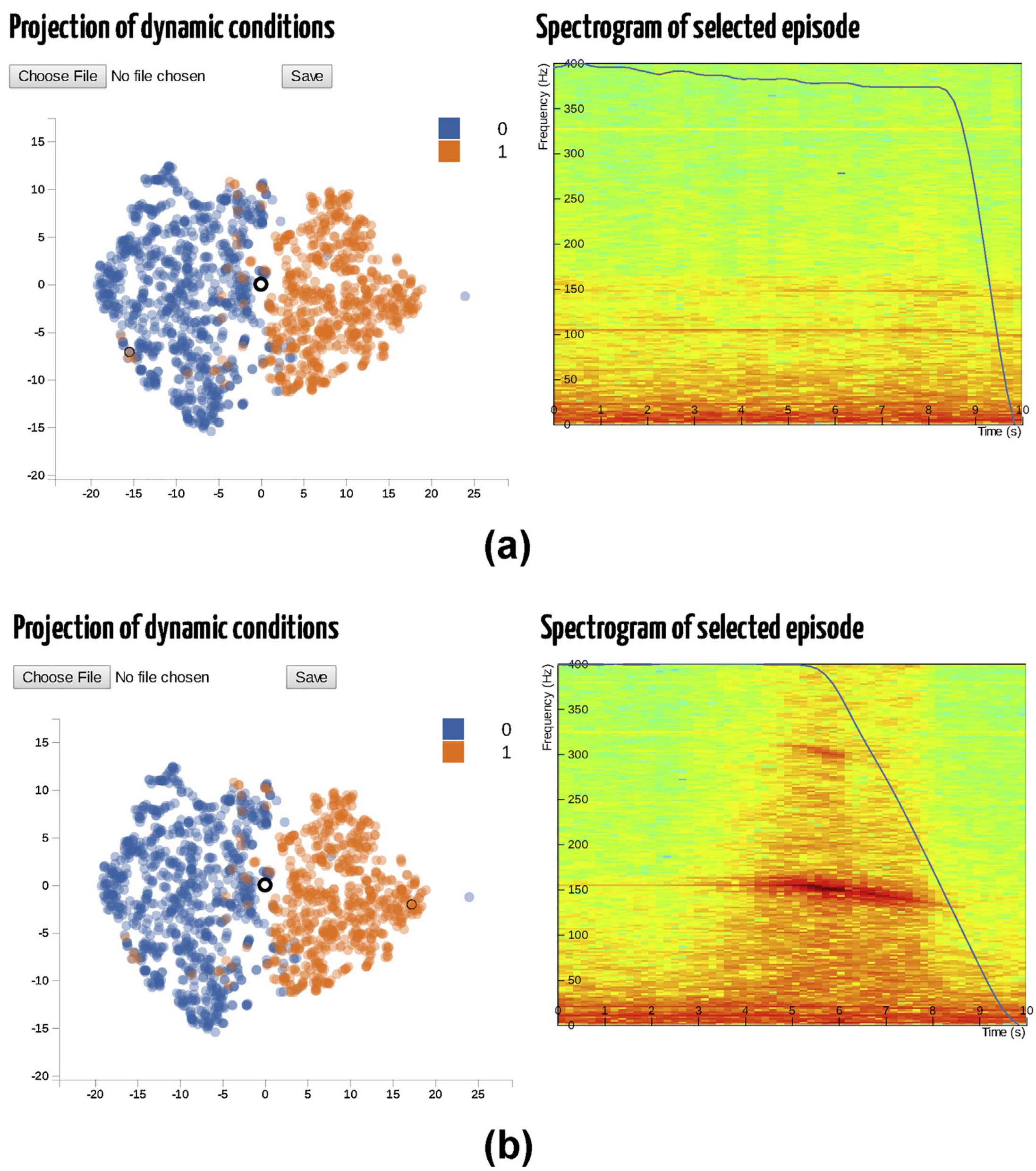

Fig. 7. Two different chatter faults explored in the application with: (a) low severity and (b) high severity.

change. To perform the dimensionality reduction, the *t*-SNE algorithm was computed with a PCA initialization, a learning rate of 900 and perplexity of 30, both empirically determined.

The exit thickness deviation is used for computing spectrograms with a segment size of 1024 samples and Tukey window. All the spectrograms were computed on a frequency band of 0–400 Hz and using the same color scale for amplitude. The longest duration of all chatter episodes was computed, allowing to establish a common time range of 10 s for all the spectrograms. All these operations are made in order to perform an easy visual comparison between all the spectrograms in the application.

4.2. Experimental validation tests

Several data processing operations can be performed by changing the values of the parameters in the identification method. They are stored in different data files that can be loaded by the user in the application. Next, some experimental validation tests obtained using the proposed application are explained. This includes information from the mill, checking of automatic chatter identification results and the analysis of several variables and their correlations simultaneously.

4.2.1. Data-based information from the mill

The dataset under analysis corresponds mostly to coils produced in 2010, but also includes some data from coils produced in 2006. We can detect differences between normal working conditions from both years by visually identifying patterns in location and color of the points in the projection.

For example, in Fig. 5a, the data projection is shown with a color scale representing the identification number of coil, that is related to the production date. The production data from 2006 are clearly visible in blue color and 2010 production data are represented in red. In Fig. 5b, the color represents the temperature of the

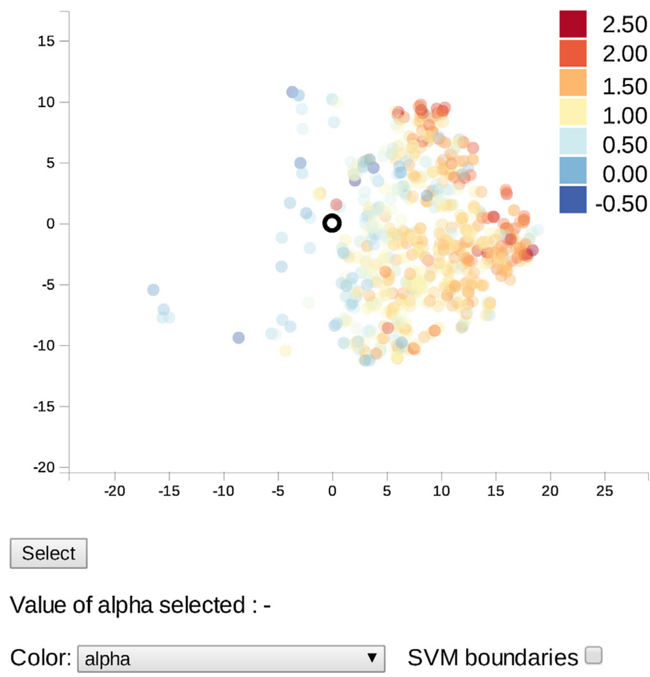

Fig. 8. Data projection with color representing the α parameter.

refrigeration water, which shows higher values for the production in 2006. Hence, this alteration in the working conditions indicate some changes produced in the cold rolling mill during those 4 years. The point highlighted in black represents the average position computed from the rest of points on the screen.

Another main difference is that the standard deviation of the vibrations measured in the 4th and 5th stands are slightly higher in 2006 than in 2010, but this difference is not noticeable in the deviation of the output thickness. Therefore, we can say that the vibrations in the mill were higher in 2006 but they were not translated to the final product.

By exploring the barcharts with the standard deviations computed in the accelerometers, we see that the vibrations between the 4th and 5th stands are quite similar, as it could be expected. In the application, the average standard deviation of the vibrations during chatter can be explored easily through a configuration in the barcharts of the time variable (5 s previous and following chatter condition) using an average aggregation function (see Fig. 6). An exponential increase of the average standard deviation of vibrations is observed in instants previous to chatter, showing the sudden nature of the fault. The highest vibrations correspond to the last stand, whose average standard deviation (nearly 0.13) is slightly higher in this 5th stand (Fig. 6b) than in the 4th stand (Fig. 6a). Using this, a quantitative threshold can be established in the vibrations of this mill for a potential chatter detection.

4.2.2. Evaluation of automatic chatter identification

Using the developed interface, the user can validate the results of the automatic identification method of working conditions. This allows to refine the parameters of the identification method quickly and assess the chatter/normal labeling for specific cases.

The spectrogram of any chatter condition can be easily visualized by hovering through the points in the 2D projection which are spatially arranged according to mutual similarities in their corresponding high-dimensional feature vectors. This allows a quick visual exploration of the chatter conditions whereby the user can identify particular conditions, that were detected by the automatic algorithm previously, but for which there might exist a reasonable doubt of them being faults.

In Fig. 7 two different chatter conditions are selected from both clusters of the projection and corresponding spectrograms are shown on the right where the bottom one (Fig. 7b) shows a more severe condition than the top one (Fig. 7a). The user can take a final decision to confirm its actual condition and also select points and remove them from the analysis in the application. Furthermore, the values corresponding to the selected point are detailed in tables (see the screenshot of Fig. 4), so that the first table shows metadata such as identification number or objective values, the second one displays the values for the variables used for computing the projection, and the last one shows the rest of available variables, like temperatures.

The same data projection is shown in Fig. 8 with color representing the α parameter values (described in Section 3.1.2) where a smooth distribution of these values computed for all chatter conditions identified is shown. Interactive revision of their spectrograms show that this α parameter can be used to evaluate the severity of the chatter conditions, which can lead to a quantitative evaluation of the fault and establish admissible thresholds.

4.2.3. Interactive coordinated views

Interactive mechanisms, such as filters dynamically defined by the user, combined with coordinated views, help to explore chatter behaviors easily. For instance, we can study chatter conditions through the vibrations produced in the mill and their effects in the final product. This is useful for confirming known hypothesis in order to test the correct working of the application. In Fig. 9 interactive barcharts show standard deviations of accelerometers of 4th and 5th stands and output thickness. Three different situations are displayed where one filter is applied to the accelerometer of 4th stand and the rest of the views are updated accordingly, with blue/orange color in the scatterplot representing normal/chatter states, respectively. In this figure, the results of

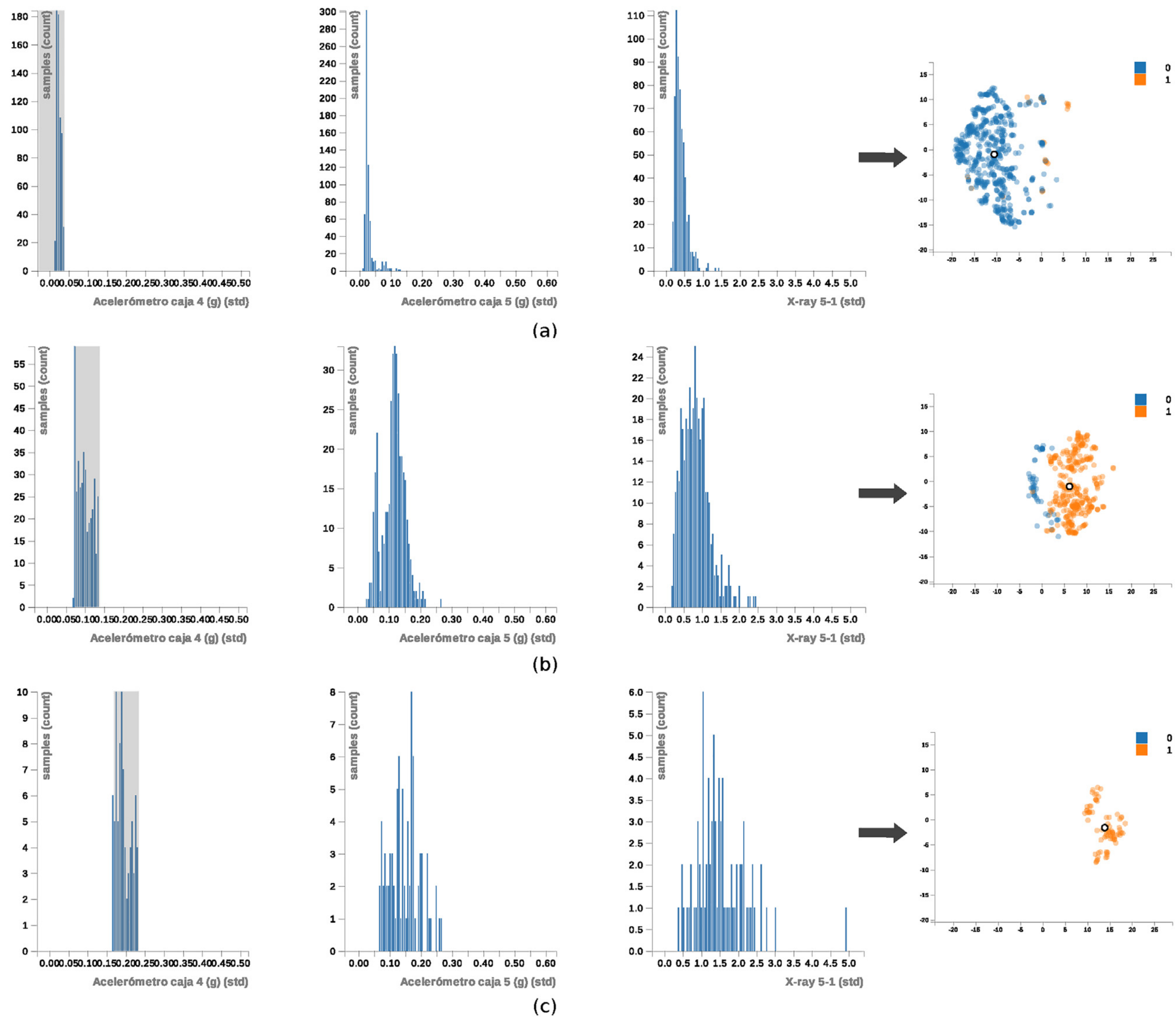

Fig. 9. Barcharts of standard deviations of (left to right) accelerometers of 4th and 5th stands and output thickness, respectively. Three situations of filtering a different range of values for vibrations in 4th stand: (a) low; (b) higher; (c) the highest values and their corresponding projection points with color showing normal/chatter condition in blue/orange, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

filtering different ranges of vibrations confirm known effects produced by chatter fault, that is, high standard deviations in vibrations of the stands correspond to chatter conditions with high deviations in the output thickness.

In Fig. 10 two rows of barcharts represent two different situations. The charts show several variables (left to right): temperature of the strip (material); 10 s of the fault; rolling velocity in 5th stand; refrigeration of the central zone in 4th stand and rolling force in 4th, respectively. In Fig. 10a, the values of the variables represent the situation with high temperatures of the strip (by a filter applied in the chart on the left) and, in Fig. 10b, they represent the situation for low values of temperature of the strip. This shows that high values of temperature of strip correspond to instants previous to fault and vice versa. This fact was checked with experts who suggested that this reduction of temperatures during the fault is caused by the decrease of the velocity performed to remove chatter. This decrease can be confirmed in the barchart corresponding to the velocity. Moreover, the influence of chatter on other variables selected by the user can be observed, for instance, in the barcharts corresponding to refrigeration and the rolling force in the 4th stand, whose values are also lower after the fault.

4.2.4. Correlation analysis between variables

In addition, the use of the mentioned coordinated views help the analyst to identify relationships between variables. Setting an average aggregation function of one variable with respect to other measure reveals correlations in the resulting chart. In Fig. 11 relationships between rolling velocity variables with others, selected by the user, are shown (left to right):

1. Variable: velocity in 5th stand; Measure: velocity in 4th stand. Obviously the rolling velocities between stands of the rolling mill have a linear correlation, that is shown in the barchart.
2. Variable: velocity in 5th stand; Measure: temperature of strip. This correlation between rolling velocity and temperature was mentioned previously in relation to the decrease of the temperature produced after chatter appearance.
3. Variable: velocity in 4th stand; Measure: refrigeration of the central zone in the stand. Here we have a correlation between the velocity and the refrigeration needed in that zone.
4. Variable: velocity in 4th stand; Measure: forward slip in the stand. In this view we can see that, in 4th stand, forward slip is higher when rolling velocity has low values.

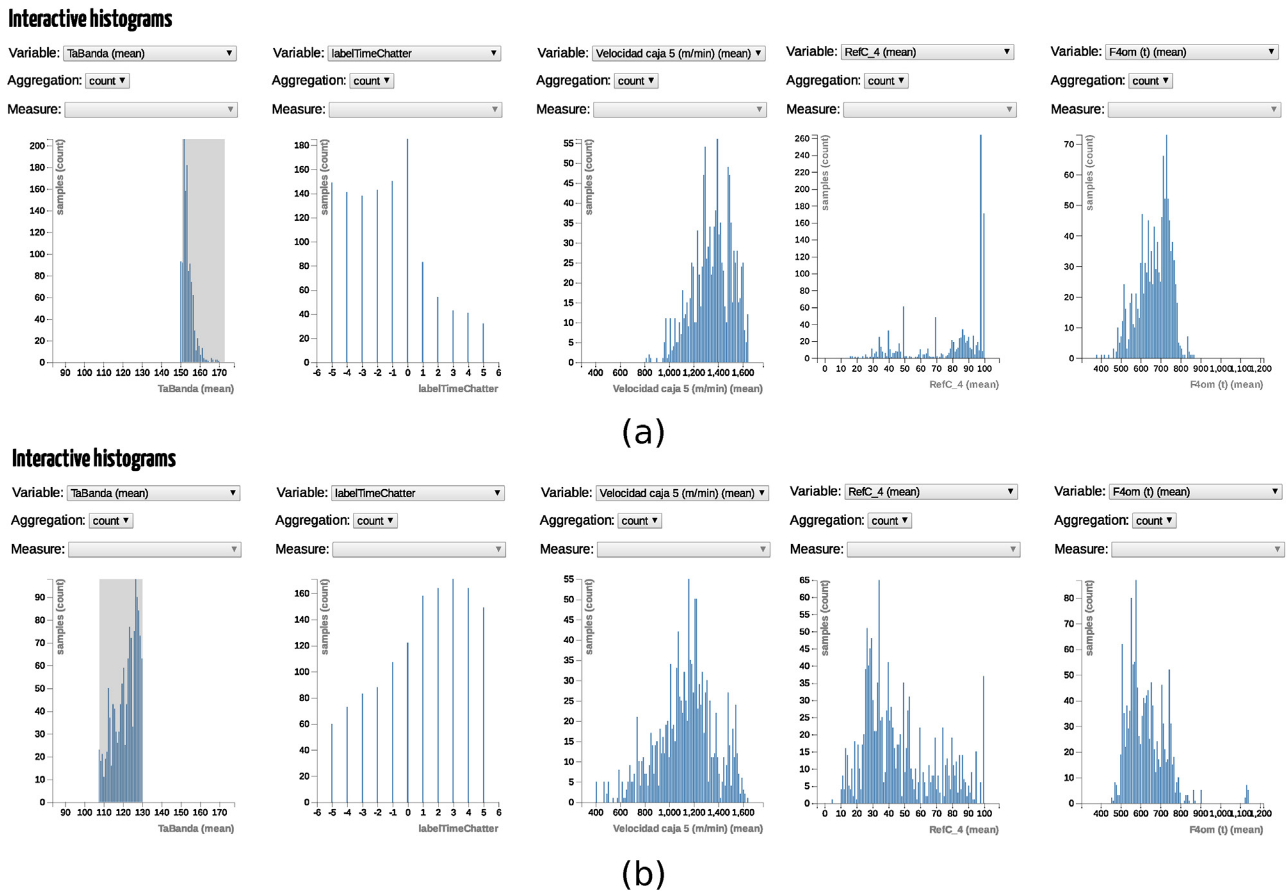

Fig. 10. Barcharts showing (left to right) temperature of the strip, 10 s of the fault, rolling velocity in 5th stand, refrigeration of the central zone in 4th stand and rolling force in 4th, respectively. Filtering temperature of the strip for: (a) high values and (b) low values.

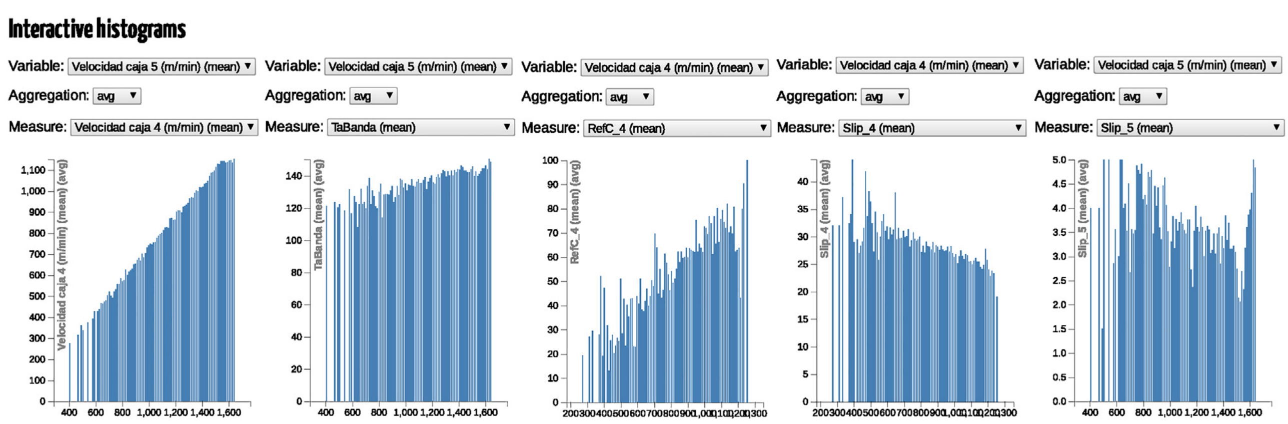

Fig. 11. Barcharts using aggregation function of average values (left to right): velocities between 4th and 5th stand; velocity in 5th stand w.r.t. temperature of strip; velocity in 4th stand w.r.t. refrigeration of central zone in 4th stand; velocity in 4th stand w.r.t. forward slip in that stand and velocity in 5th stand w.r.t. forward slip in that stand.

5. Variable: velocity in 5th stand; Measure: forward slip in the stand. In this case, in the last stand of the mill the relation between rolling velocity and forward slip is quite similar up to a specific value of velocity, where the correlation changes.

This correlation analysis is a powerful method to infer existing relationships between several attributes related to chatter appearance. The visual nature of this approach provides a direct way to obtain information about the relationships among the variables, such as the slope of a linear relation as well as local correlations, conditioned to specific ranges of process conditions.

5. Conclusions

In this paper, a visual analytics approach is proposed for exploratory analysis of the self-excited unstable vibrations (chatter) produced in a cold rolling process, which allows for a very novel type of analysis that is particularly suitable in the steel industry. Data from a real industrial facility were processed to identify normal and chatter conditions automatically using domain knowledge, and a vector of descriptive features was computed for 1-s segments in the identified conditions for a set of available variables. These descriptors include also other parameters related to the dynamics of the process. Then, a procedure was applied to obtain a map of the dynamical conditions ordered by similarities using machine learning methods such as clustering or dimensionality reduction.

A web application prototype was developed that presents data corresponding to production of 4102 coils in a visual way through 2D maps of dynamic states, spectrograms and bar charts, providing the user with mechanisms of fluid interaction. This tool helps to obtain a general view of normal/chatter conditions in the process, and also analyze details on demand of any chatter state identified. Interactive barcharts are used for exploring the whole set of the available variables where user-driven filters show behaviors of the industrial process efficiently. Coordinated views help to find relationships between dynamical states and the values of the variables involved. Aggregation by average functions showed correlations between variables that were used for analyzing the relations of rolling velocity between several variables.

The proposed tool can be considered as a framework for interactive exploration of a broad set of rolling mill variables relevant for the chatter in a quick and comprehensive way, showing differences between fault/normal conditions. The coordinated views and interaction mechanisms allow the user to take part in the analysis cycle and make it possible to exploit the domain knowledge. This leverages a better understanding of the process and supports its evaluation. This can be useful, for example, in quantifying various behaviors for this specific mill or as an assisting method for the experimental refinement of the automatic algorithm for chatter detection.

The approach used in this article, based on the use of dimensionality reduction techniques and interactive data cubes that allow filters and aggregations to be carried out on multivariate data, can be adapted to other industrial problems and admits numerous generalizations that may constitute interesting future lines of research. Some possibilities involve the search for application niches in other fields or the implementation and application of advanced aggregations in the data cube, which would allow the identification of systems, or multivariable models, conditioned to filters defined by the user.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.compind.2018.08.008.

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