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ORIGINAL ARTICLE

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An approach to the analysis of thickness deviations in stainless steel coils based on self-organising map neural networks

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Abstract The aim of this work is to classify the sections of coils produced on a cool rolling mill that have an irregular thickness pattern, in order to achieve a homogeneous thickness in each coil. In order to do this investigation, we have employed a self-organising map (SOM) of neural networks, a new segmentation and clustering algorithm, filters to reduce the noise and, finally, a classification calculated from the difference between the value of each sample taken and the average of them all. We have introduced an alternative approach, with improvements in the segmentation and clustering steps, which has been successfully applied in an industrial production line. Some of our limitations and future areas for investigation are also included.

Keywords Neural networks applications · Self-organising maps · Data series analysis and clustering

1 Introduction

Thickness is, among other things, an important property of the stainless steel released by flat rolled production lines and it must be closely supervised by control quality activities with high-precision instruments. It is expected to be constant along a production unit or coil, which can be several hundreds to several thousands of metres long, depending on its thickness and some other factors.

Traditionally, the process of measuring the thickness of production line stainless steel sheets has been done in a manual way and at only a few points on the sheet. Now, because of the improvements in quality control, a non-contact measuring system is required that works in a continuous manner during the production process. With this in mind, we have designed and installed an autonomous measuring system based on twin laser sensors [1, 2].

Coils are required to have a thickness that is as close as possible to the nominal desired value, or at very least, to have a breadth within the tolerance limits. The homogeneity of their gauge, without changes and abrupt slopes in their value, is essential.

The detection of those areas that are outside of tolerance limits is trivial using a direct comparison, but it is more complicated to detect thickness abnormalities or irregularities whether they are between these limits or not. We must bear in mind that the values obtained by the measuring instruments are contaminated by noise, both mechanical (due to the movement of the coil in process inside the non-contact instrument) and electrical. Also, the instrument has a resolution sufficiently high to detect gauge fluctuations produced by the previous rolling mill process [3].

In order to achieve an automatic analysis of the acquired data, a classification system based on neural networks was conceived [4]. We used a kind of unsupervised self-organising map (SOM) neural network to detect and classify different patterns in the abnormalities of thickness [5–7]. We obtained the SOM from a sample of completed measured coils acquired by the measuring equipment over the period of a month, in which all the different gauges were processed.

In this paper, we present the detailed procedure followed in order to obtain and apply an SOM. We also describe the segmentation, the making of the SOM and the steps that were taken in clustering. The results of its application on real coils are also described.

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2 Materials and methods

The measured and classified stainless steel coils have a thickness range of between 0.5 and 6 mm, a width range of between 1,200 and 1,550 mm and a length anywhere from several hundred metres to several kilometres. In our sample, we measured coils produced by Acerinox Inc. over the period of a year, on an order of 6,000 cases.

The software tools used to implement the classification program were Matlab 6.0 and *The Self-Organizing Map Program Package* made by Kohonen et al. [8], which were capable of implementing the neural network techniques that were needed.

The laser measurement system (Fig. 1) ascertains the thickness of the coil at regular time intervals so, depending on the speed of the production line, it will obtain either more or less readings from a given length. A significant problem which we face when dealing with a non-contact thickness measuring system and moving sheets is how to reduce noise levels (whether they be electrical or due to vibrations and changes in the position of the sheet). So, the series of compiled data must be processed to filter out random or impulsive noise [9, 10]. A median filter is applied and we also take the average of all measurements in a metre length interval because the thickness is expected to be quasi-homogeneous due to the nature of the rolling mill process.

Initially, the difference between the real and the desired thickness was appraised. The method adopted has some drawbacks; for example, a coil that regularly differs in thickness from what is desired by one customer may be wrongly classified, while it could be perfect for another customer. Also, we are focussing on those zones where the thickness deviates. It is for these reasons that we analysed and classified the difference between each sample value and the average of them all.

2.1 Segmentation

The SOM neural networks work with input data vectors of fixed length. In this case, however, the stainless steel sheets are of variable length, so a segmentation of fragments of a fixed length is needed. These fragments will then be classified independently.

Based on previous investigations [4], and on the analysis of the typical length affected by thickness instabilities, we have concluded that, for our application, the best dimension for the segments is at least 40 m. We have worked with different segment lengths, from 40 to 200 m, and we have found that a range between 40 and 70 m provides the best results. Finally, we chose 40 so that we were not joining two different areas of divergence in thickness in the same segment, which would make it more difficult for the SOM neural networks to detect a pattern.

Previously, we divided the coil into a series of adjacent segments, from its beginning to its end. This fixed segmentation approach (Fig. 2) has a major drawback because a given anomaly in thickness could be split into two adjacent vectors, hindering the neural networks' ability to classify. Therefore, the same non-stable area could be classified differently, depending on the part of the vector where it is placed. So, we adopted another strategy; a new segmentation algorithm.

In order to improve that procedure, it is essential to appropriately detect and segment any kind of thickness deviation. Due to the ignorance of the exact shape of the thickness instabilities, the new method (Fig. 3) works by detecting abrupt slopes. An abrupt slope is defined as the

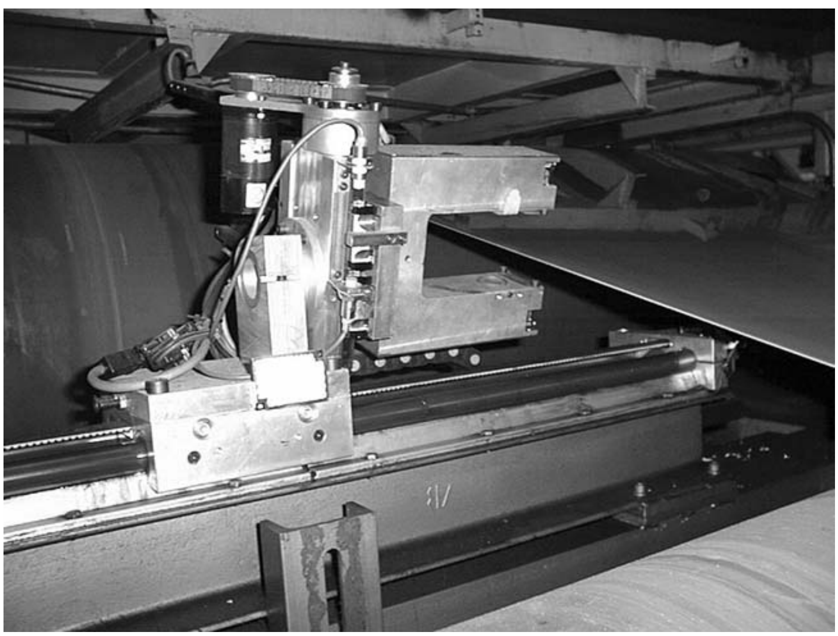

Fig. 1 The laser measurement system

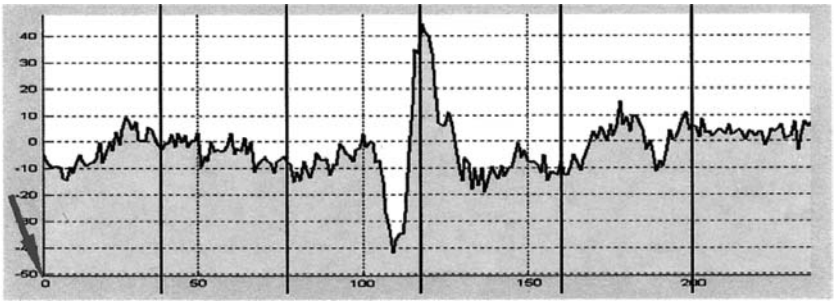

Fig. 2 A coil segmented in a series of adjacent segments

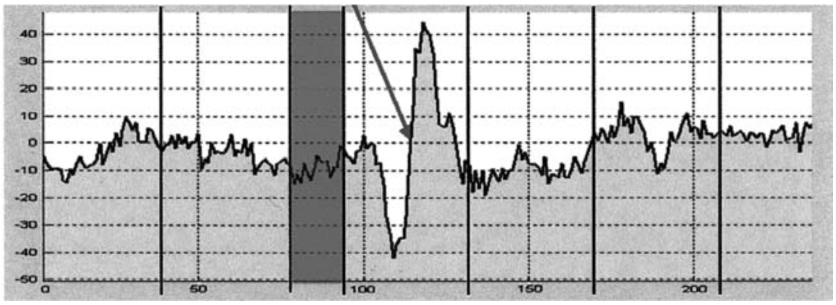

Fig. 3 A coil segmented by the new segmentation algorithm: firstly, the abrupt slope is detected and appropriately segmented and, finally, the remaining data are segmented from left to right. The dark zone area is not covered by this algorithm

zone where the thickness variation in X metres is higher than Y microns. For our application, we have settled on the values of 5 m and 25 microns for X and Y, respectively, in order to avoid the detection of noise as thickness variations.

We must take into account the fact that two abrupt slopes could be located close to one another. The maximum slope point of the abrupt slope is situated in the middle of the segment, and the procedure then checks if there is another one within a range of 15 m. So, if two of them are closer than 15 m, they are considered to be the same inconsistency in thickness and both will be part of the same segment. Otherwise, they become part of different segments, despite the fact that they may be overlapping during some length.

The new segmentation algorithm is divided into the following steps:

1. First of all, every abrupt slope is detected
2. Then, those zones around abrupt slopes are segmented in such a way that the maximum slope point is located in the middle of the segment
3. Finally, the remaining coil is covered, from left to right, with adjacent vectors

As a consequence of its application, some small zones could be overlapped by two segments and others not covered by any at all (shadow zone in Fig. 3). But the non-covered zones will always be near to a segment with an abrupt slope, and it is certain that it does not contain any thickness abnormality. Therefore, it does not matter if this zone is not analysed or classified.

The advantage of this method is that it prioritises the appropriated segmentation of non-stable thickness areas and, therefore, it reduces the loss of relevant information. In addition, this method universalises the segmentation of abrupt slopes so that the SOM neural networks can easily detect shapes and patterns in the thickness deviations.

2.2 SOM making

In the process of creating an SOM, the segments are represented by vectors, with each being an element of the thickness value from fixed length intervals of the original stainless steel sheet. After many tests, we decided to use vectors of 20 elements, where each one represents the median thickness at 2-m intervals. The reason for this decision is not only because the SOMs created by those vectors provide the best results, but we are looking for inconsistencies over several metres. On one hand, the measuring system is not able to detect very small deviations with precision, and on the other hand, deviations of less than a metre in coils 2 km in length are insignificant, while deviations over several metres considerably reduce the quality of the coil.

We will now describe the process of making the SOM, through which we constructed and trained a map. The Gaussian function was chosen as the neighbourhood function, and a hexagonal structure as the topology of the map.

First of all, the number of map units must be determined. A heuristic formula is used based on [2]:

$$\text{Map\_units} = 5 \times \text{dlen}\hat{}0.54321 \times \lambda$$

where dlen represents the number of vectors used in the training process and λ controls the size of the map, with $\lambda=4$ and $\lambda=0.25$ for a "big" and "small" map, respectively.

After the number of map units has been determined, the map size is fixed: firstly, the two biggest eigenvalues of the training data are calculated. Secondly, the ratio between them is assigned to the side lengths of the map grid. And finally, the actual side lengths are set so that their product is as close to the desired number of map units as possible.

Then, the SOM is initialised by a linear initialisation along the two greatest calculated eigenvectors. And finally, the SOM is trained in two phases: firstly, the rough training, and then later, the fine tuning.

We have constructed and trained some SOM neural networks using more than 500 real coils measured over the period of a working month on a production line in the Acerinox factory in Algeciras (Spain). From that data, we have obtained approximately 20,000 vectors. We worked with different map sizes and, based on the formula proposed by Kohonen with $\lambda = 4$, we have obtained SOMs that are more suitable for our purposes. Smaller maps do not classify some types of deviation because of their reduced number of neurons, and larger maps do not classify more types of instabilities than the SOM used, and they complicate the clustering step of the procedure.

We have made some SOMs with data from different months and have obtained similar neural networks.

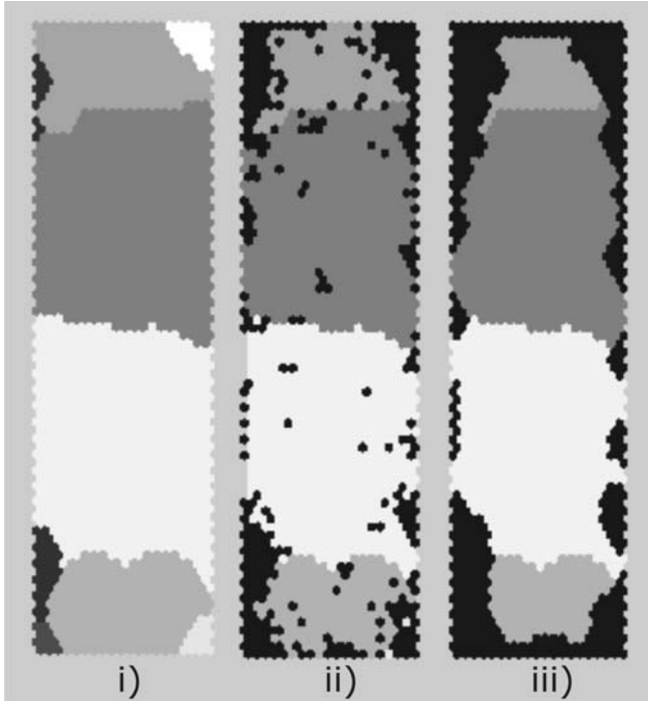

Fig. 4a–c The clustering process. **a** The standard Kohonen division. **b** The marking process. **c** Abnormality cluster

2.3 Clustering

After an SOM is created and trained, a neuron map is obtained. Each neuron has a hexagonal structure and has up to six neighbours. It is necessary to create another process to group neurons that classify similar patterns of thickness deviations together. The final step in the process of making a classification system is clustering.

The clustering process groups together neurons whose Euclidean distance between its vectors is smaller. We have noted that the use of the standard division made by the Kohonen Package (Fig. 4a) is not an appropriate solution in our case, because it creates an excessive number of clusters related to thickness variations. In addition to this, what we require is the creation of a unique cluster that includes those neurons associated to instabilities, and this is something that the standard clustering does not detect.

So, we have developed an approach that works on SOM divided by the standard clustering. The idea is to detect all abrupt slopes of a coil population different from the one used in the training step. Then, we create and superimpose an "abnormality cluster" containing all neurons that classify those abnormality populations. This new cluster can cover some clusters made by the standard method.

A considerable problem we have to deal with is the non-univocal relationship between abrupt slope and thickness deviation: almost every abrupt slope is a thickness deviation, but not all thickness deviations are characterised as abrupt slopes. Therefore, it is necessary to adjust the neuron map in order to select those neurons which actually classify thickness deviations and reject those that do not. This process is based on one of the most important characteristics of SOM: close neurons classify similar vectors. In addition, a study of the behaviour of the SOM we created concluded that most of the neurons that classify thickness variation are located on the periphery of the neuron map.

The fine-tuning method is based on image processing [11]: erasing and adding neurons to the new cluster, depending on their location in the map and on the number of their neighbours that belong to it. This method is divided into two processes:

1. First of all, a smoothing step is taken: those neurons close to the border of the map which have four or more neighbours marked as belonging to the new cluster are very likely to also belong to it. So, they become part of this new cluster (Fig. 5a), as do neurons that are not on the periphery but which have at least five neighbours which belong to the new cluster.
2. Finally, the erasing step is applied: those neurons marked as belonging to the new cluster that are located close to the periphery and have three neighbours or less will not belong to the cluster (Fig. 5b). And also those not in the periphery which have at least two neighbours marked.
   For each step, the map will be covered from top to bottom and left to right, except for those neurons on the border of the map that are not modified.

Summing up, the new clustering algorithm is divided into three steps:

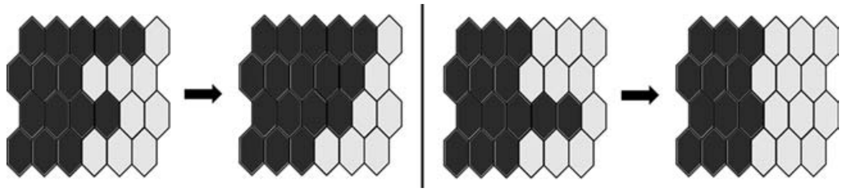

Fig. 5a, b The tuning process. *Dark* colour neurons belong to the abnormality cluster. **a** The *left* picture shows how the smoothing step works, marking two neurons that have more than four neighbours. **b** The *right* picture shows the erasing step: two neurons that have less than or equal to three neighbours have been erased

1. First of all, from a population on the order of 1,000 coils, every abrupt slope zones is detected and appropriately segmented
2. Then, all these segments are classified by an SOM, marking all the winner neurons (Fig. 4b)
3. Finally, the tuning process is applied to it (Fig. 4c)

3 Results

Using the explained methodology, an SOM has been created which divides into five clusters (Fig. 6) that classifies different shape patterns: *regular thickness*, *very irregular*, *irregular positive* and *irregular negative levels 1* and *2*. The *very irregular* pattern is associated with thickness abnormalities and its cluster is located in the periphery of the neuron map (Fig. 6b). The rest of the clusters were created in the standard clustering process.

This SOM has been used to analyse measured coils. This classification system is able to detect thickness deviations and segments whose values differ from the average thickness. They will be classified depending on their shape and on the difference between their values and the average thickness values, respectively. We present two examples of its performance in Figs. 7 and 8.

Figure 7 shows a measured coil of more than 2,000 m in length. It has a thickness scale of 10 microns. The classification system has detected that the greatest deviations in thickness occur in the middle and at the end of the coil. There is a small deviation of less than 20 microns at the beginning (mark 1) classified as *irregular positive*, but it is not big enough to be considered as *very irregular*. In addition, there is a concave curve (mark 2) detected and classified as *irregular positive*. After that, there is a long convex curve (mark 3) divided into seven segments. These segments are classified as *irregular level 1*, *level 2* or *very irregular* depending on the difference between their thickness and the average.

Figure 8 represents the initial part of a coil up to the 400-m point. The thickness scale is 50 microns, different from Fig. 7. There are several thickness deviations classified as *very irregular* at the beginning, middle and at the end of the coil.

4 Conclusions, limits and future areas of investigations

We have introduced an alternative approach based on neural networks with improvements in the segmentation and clustering steps. It has shown a greater efficiency and accuracy than the other methods described in previously cited papers. And finally, it has been applied successfully in an industrial production line.

The main results obtained from this investigation are:

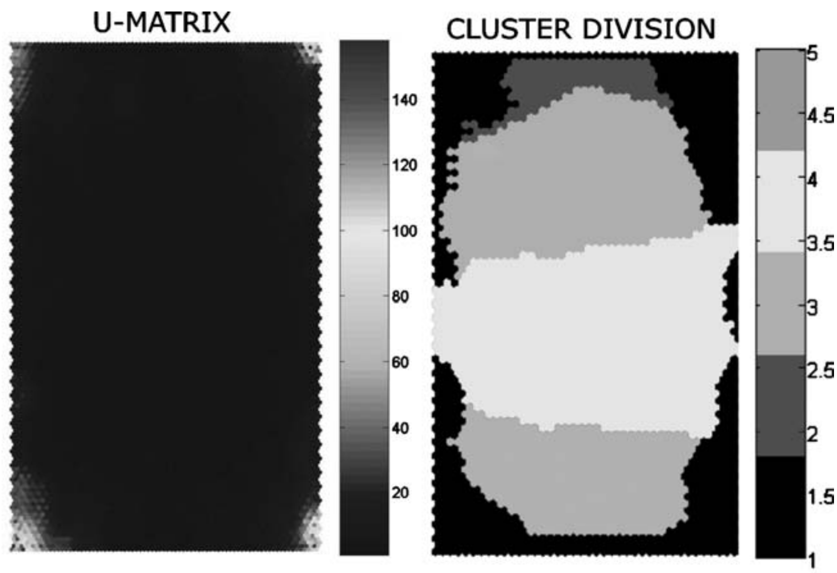

Fig. 6a, b The trained SOM. **a** The U-matrix of the created SOM using 20.000 vectors. **b** The clustering division made by the proposed method

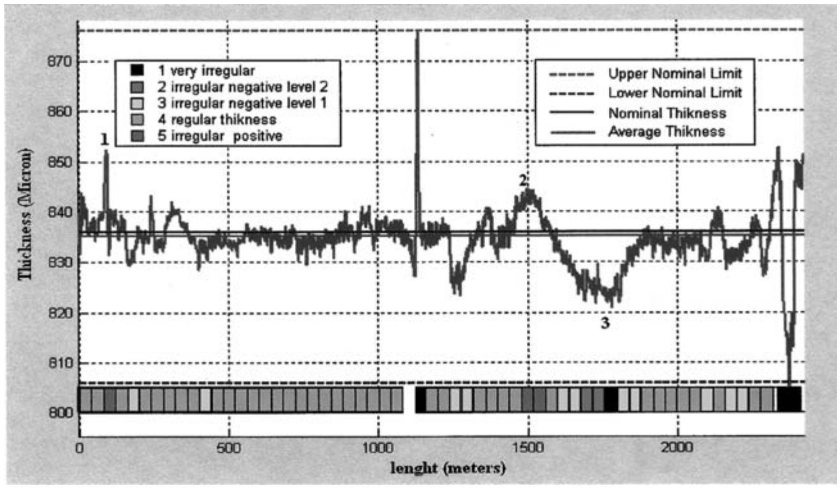

Fig. 7 A coil thickness graph and its classification

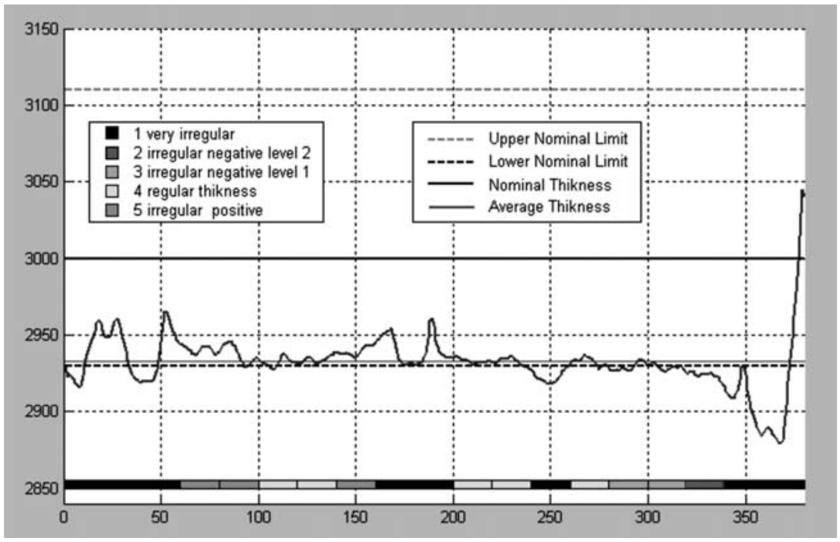

Fig. 8 A fragment of a coil with 3,000 microns nominal thickness graph and its classification

– A new segmentation algorithm, based on the appropriated segmentation of abrupt slope zones, which reduces the loss of the relevant information
– An improved clustering algorithm that superimposes a new cluster including all neurons, which classify thickness deviation
– A filter has been applied to the thickness data series to eliminate the noise and to adapt the information in order to get a better classification
– The SOM creation process has been improved through the use of a better quality of training data
– A successful classification of stainless steel sheet has been obtained

At this moment, we have centred on the global classification of each segment, but we are unable to ascertain what kind of abnormality it is affected by. Additional work is required in this field and we propose the use of supervised neural networks in future investigations. Also, the use of segments of variable length fitted in homogeneous vectors would be recommendable for this purpose. The analysis we carried out on a coil is based on the segmentation of the thickness data series, but it would be beneficial to have a more compact classification of the whole coil. It would be interesting to undertake a new line of investigation with this objective in mind.

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