Characterizing surface quality of randomly textured galvanized strip.

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Introduction

Siemens VAI is moving one notch forward its technology edge in Automatic surface inspection, on SIAS® systems. The conventional two step method of detection / classification relies first on fast real time algorithms to pull out "objects" of interest, then on powerful classification calculations to adequately reject pseudo-defects and sort the pertinent defects in appropriate families. SIAS® systems have long improved the original simple detection threshold recipes by "flying in close-cropped-mound", i.e. automatically adapting detection sensitivity to background texture, on both hot and cold band applications.

However, on materials displaying complex patterns that are random in appearance, detecting subtle local defects or describing textural variation turns out to be a rather difficult task.

Siemens VAI has initiated a cooperation with the world renown Mathematical Morphology laboratory (CMM) of the *Ecole des Mines de Paris* to progress in this direction. Interesting and directly applicable results were obtained by the *CMM* researcher team on complex hot and cold band surfaces. They here-after present a short sample of their original and special methods applied to spangled galvanized strip, describing texture and demonstrating its potential in the evaluation of textural variation across the surface. The study was made possible thanks to the "Digital Coil Recording" (DCR) feature equipping SIAS® systems, permitting the uncompressed recording of the video stream of an entire coil as a full image, when desired. Large amounts of images were thus processed in this aim.

1. Pixel texture description

For the calculation of texture descriptors, each pixel of images is described by a vector accounting for information in its neighbourhood, at different scales. This generates for an image a cube having two spatial dimensions and a descriptor dimension. Among the numerous image analysis tools, two families of descriptors are used at this level: the curvelets and morphological sizing by opening and closing transformations.

Curvelet transform

The curvelet transform is a higher dimensional generalization of the wavelet transform designed to represent images at different scales and different angles (Candes and Donoho, 1999). The use of this transformation to characterize the texture in an image is relatively recent (Elad et al., to appear). The curvelet filter bank is in essence a set of bandpass filters with range and orientation selective properties. Typically, is applied a linear filtering in each 100x100 neighbourhood of every pixel by 26 curvelets with different orientations and ranges. For illustration, figure 1 presents three curvelets in both spatial and frequential domain. A local energy function is applied, for the purpose of transforming areas in each channel where the band pass frequency components are strong into a high constant gray level and areas where it is weak into a low constant gray level. The outputs of this function are the first part of the texture descriptors of each pixel.

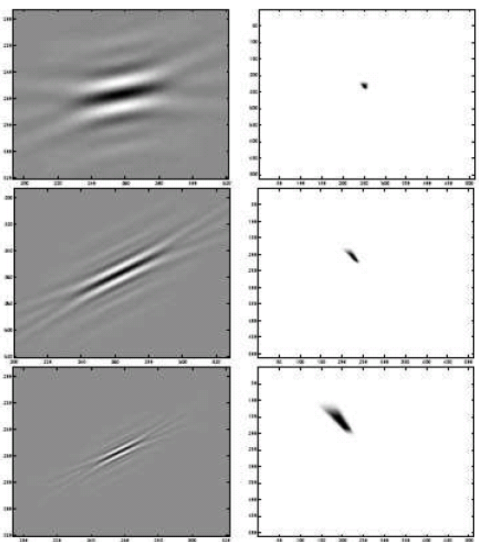


Figure 1: *3 curvelets in the spatial and frequency domains.*

Morphological granulometry

The morphological operators which are used are non linear filters (Serra, 1982). The opening, obtained by an erosion followed by a dilation by a given structuring element, keeps bright parts of the image which can contain the structuring element, while the closing operation (dilation followed by an erosion) keeps dark zones in an image larger than the structuring element. Applying successive openings (respectively closings) by structuring elements of increasing sizes, progressively makes disappear at increasing scales features in the image. It is on this morphological property that the descriptor is constructed.
For a given type of structuring element (square, horizontal or vertical segment), we keep the difference between the open images at steps n and n+1, as well as between the closed images at steps n+1 and n. A series of sizes of structuring element is used, [2, 4, 8, 16, 32] *2+1 in the present case. Figure 2 presents the descriptors images obtained for a square structuring element. Therefore each pixel is described by a vector with 24 morphological components (4 sizes for 3 structuring elements and 2 operations), generating the second part of the texture descriptors.

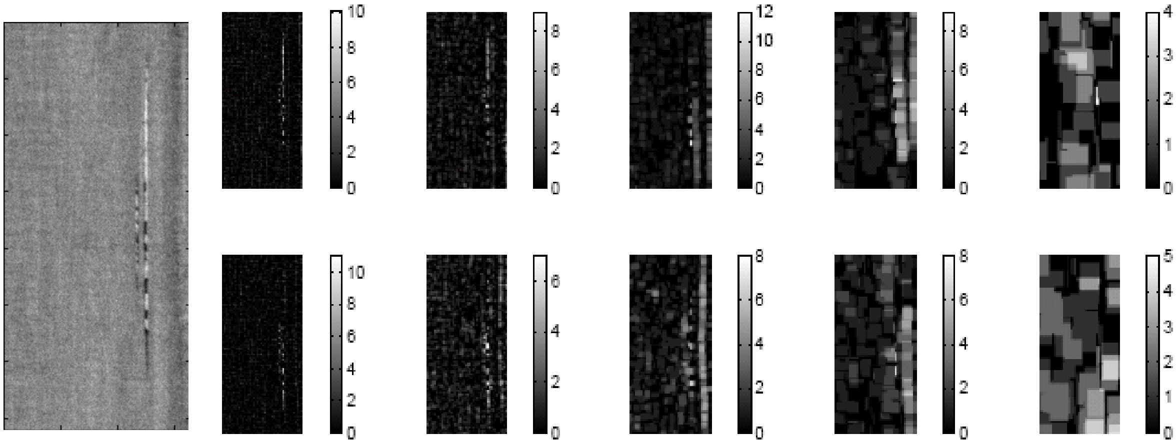
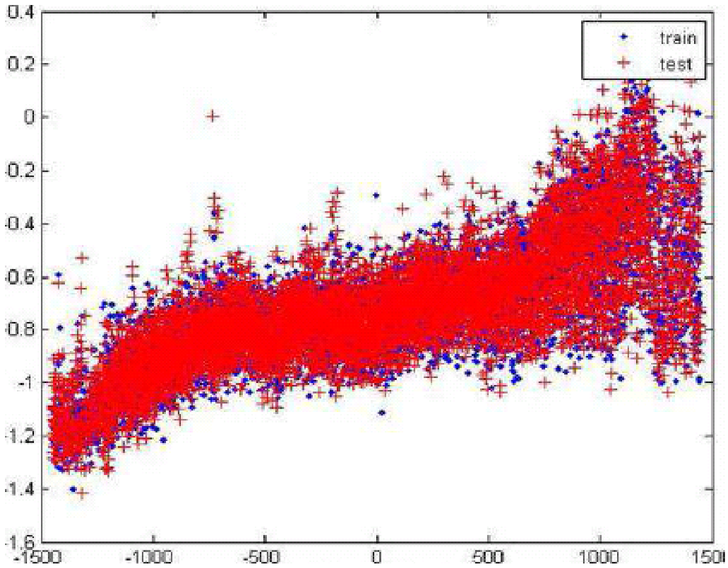


Figure 2: *Example of morphological texture descriptors for a square structuring element*

2. Correlation between the textural properties and the position on the surface.

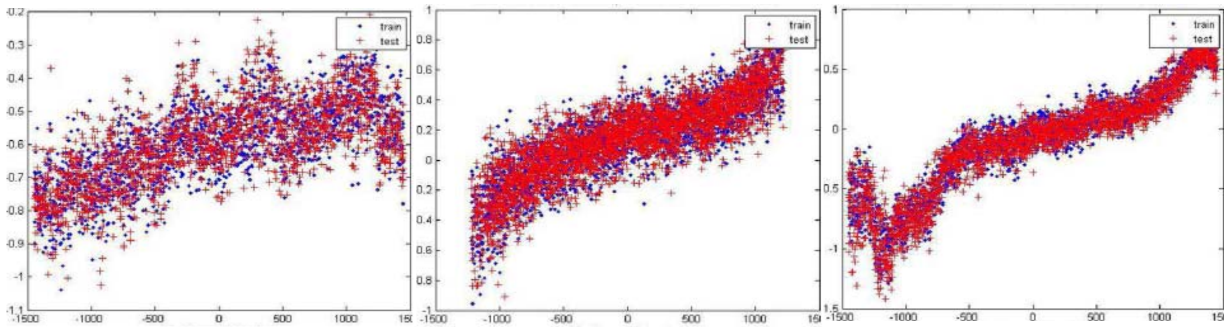
We studied the existing variations of texture on spangled galvanized steel strip, on an industrial galvanizing line. We started from three sets of images with different textural properties in the band width, identified during the production process.

The descriptors as presented above are calculated. They are averaged in boxes sizing 100 pixels down web per 10 pixels cross web. Then a multivariate canonical correlation analysis (CCA) between the descriptors and the position across strip width is made. This analysis is a method of measuring the linear relationship between two multidimensional variables. It finds two bases, one for each variable, that are optimal with respect to correlations and, at the same time, it finds the corresponding existing correlations (Hastie et al., 2001). Several analysis are carried out.



Processing all the data sets together, we test the presence of texture variation across the surface. Figure 3 shows a weak but systematic correlation between the texture of surface and the position across the strip width. The origin of this correlation could have come from the acquisition system (camera angle, non-uniform lighting) or rather, in the present case, from an asymmetry in the zinc coating process.

__Figure 3:__ Result of CCA for all data sets. X-coordinate corresponds to a linear combination of texture descriptors and Y-coordinate is the position on the band width (in pixels). The blue dots are training data points and the red crosses are test data points.



(a) (b) (c)

__Figure 4:__ Results of CCA for separately processed data sets. (a) weak variation of texture; (b) small variation of texture; (c) strong variation of texture. X-coordinate and Y-coordinate are similar to Figure 3.

The different sets of images are processed separately. Figure 4 shows the results of the correlation. This analysis allows us to detect variations which were anticipated: a weak variation of textural properties on Figure 4.a, a small one on Figure 4.b and a strong one on

Figure 4.c. This analysis is powerful to identify textural variations across the band, even when those variations are weak and can hardly be detected by a human inspection.

Conclusion and perspectives

The here-in pixel texture descriptor tools, as presented by the CMM research team, are promising for many other applications, such as texture classification and light defect detection in strongly textured surfaces. This development is only one of the new features Siemens VAI Metals Technologies is incorporating in SIAS® upgrade plans for Automatic Surface Inspection systems in the near future.

The sixty metals production sites already successfully using the powerful SIAS® systems may stay sure Siemens VAI is committed to the development and servicing, over the full life cycle, of their surface quality management tools as well as their other capital investments, for many years to come.

References

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