Neural Networks tracking large-diameter pipes: Intelligent image processing in a rough industrial environment

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ABSTRACT: We developed a new image processing system for non-contact monitoring of material flow based on neural computing. The system is applied to track large-diameter steel pipes in a rought industrial environment. It observes an area of 70x20 m^2 with three black and white standard CCD-cameras. To manage the inhomogeneous illumination conditions in the presence of daylight, a new 'frame merging' technique is used. The cameras are mounted at the corners of the observing area and they produce perspectival distorted images of the scene. After a geometrical correction and a low pass filtering of the images, pipes in each image are detected by multilayered perceptrons. The training of the perceptrons is done offline by supervised learning from examples.

KEYWORDS: neural network, frame merging, object recognition, image processing

INTRODUCTION

Image processing is a field of growing importance in industrial automatization. Typical examples of applications are workpiece positioning tasks with high resolution cameras, quality inspection after automatic assembling or optical failure recovery with intelligent techniques. Usually indulstrial processes utilizing such techniques have to be (re)designed to fit the requirements of image processing (e.g. bright illumination, avoidance of disturbing light and good contrast to the background). We will introduce an application of image processing for monitoring material flow that has been installed supplementary to an existing farbrication process, placed in a rough industrial environment [Fecht, (1999)].
In a manufactory of large-diameter steel pipes the material flow within an area of 70x20 m^2 is monitored by our image processing system (see fig. 1).

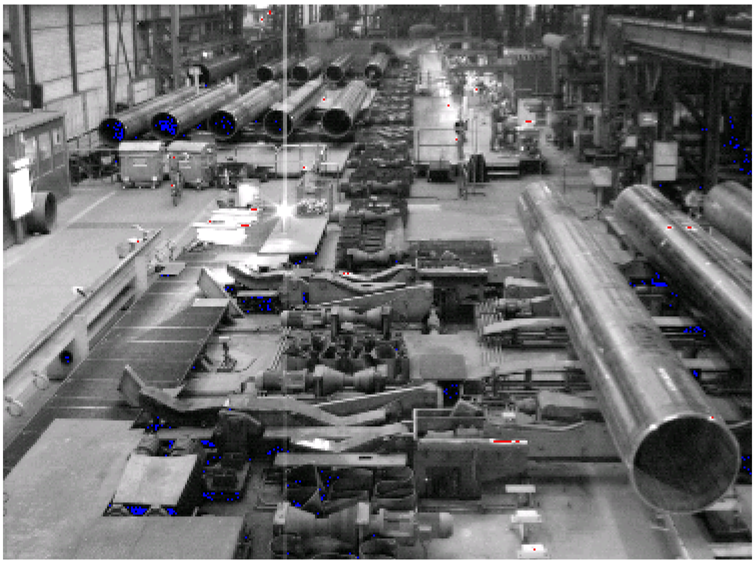

Figure 1: Area with material flow monitoring by the new image processing system.

The pipes can be moved in their axial direction on rolls and perpendicular on lateral transport devices. They must be

detected when they enter the area and tracked until they pass a defined position. A roboter placed at that position uses information provided by our system to sign the pipes correctly with their individual data.
As one can see from fig. 1, the illumination conditions in the area are not well suited for a image processing system. At daytime sunlight can flood through the glass ceiling. In the dark, sodium lamps emitting yellow light are used. Additionally there can be heavy showers of grind sparks or welding spots. The surfaces of the pipes consists of polished steel and rust in arbitrary combinations. Pipe dimensions range from 0.6 m to 1.6 m in diameter and from 9 m to 18.5 m in length.
Because of the immense variability in outlook for observation objects and background, the detection of pipes in the camera images is a difficult task. Therefore advanced techniques with high error tolerances have to be utilized. Our approach uses neural networks as intelligent classifiers.

IMAGE PROCESSING

For the image processing a huge amount of raw camera data has to be reduced stepwise to abstract coordinates of pipes in the scene. This is performed by connected processing objects each representing a single processing step (Fig. 2).

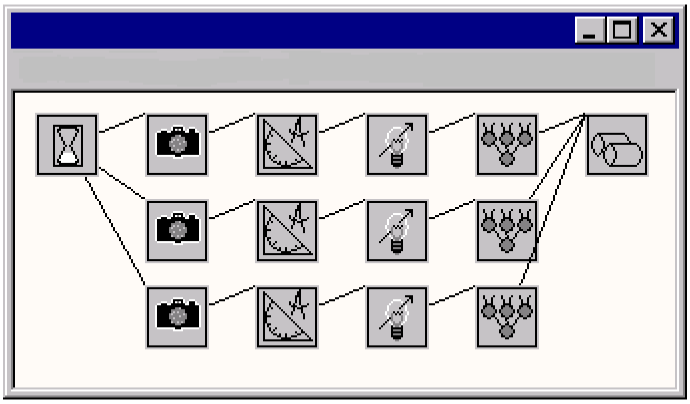

Figure 2: Connected objects representing single image processing steps.

In fig. 2 the image processing progresses from the left to the right.
 The first object, the trigger, controls the timing of the processing cycle and the syncronization of the image aquisition.
 The aquisition of the raw image data from the cameras is encapsulated by the camera source objects. Furthermore, the camera sources perform a preprocessing to overcome the difficulties arising from the inhomogeneous illumination conditions. For a single image used for further processing, two pictures with different exposure times are taken from each camera.
On the picture with the long exposure time (fig. 3, left), the darker parts of the scene are rich in contrast. In the brighter parts, the charge saturation of the CCD elements are reached and any contrasts vanish. Conversely, the picture with the short exposure time (fig. 3, right) shows contrasts in the brighter parts but only poor contrasts in the dark. By rescaling the gray values of the two pictures one gets a ‘synthetic’ image (fig. 3, center) with contrasts in the dark as well as in the bright regions.

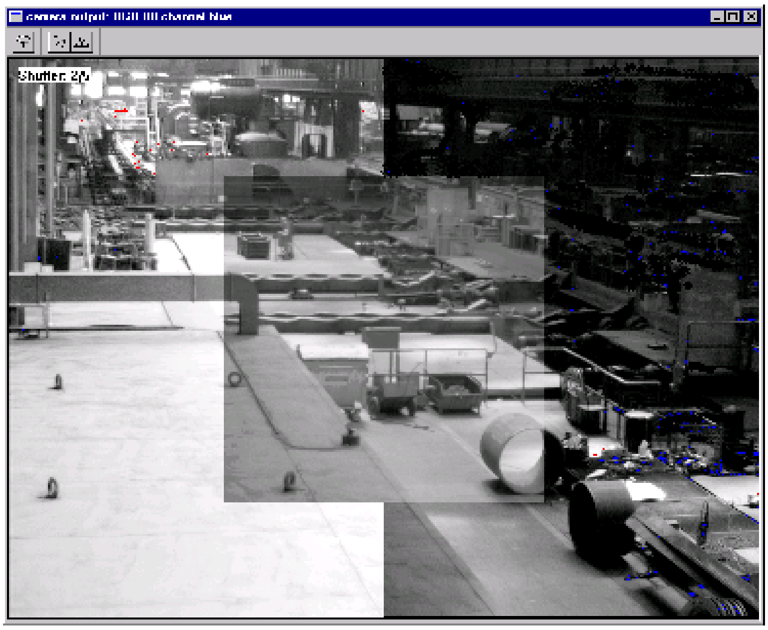

Figure 3: The ‘frame merging’ technique synthesizes an image with enhanced dynamical range from two images with different exposure times.

Subsequent geometric transformations convert the perspectival distorted images to a stretched bird’s-eye view (fig. 4).

Figure 4: Geometric transformation to a bird’s-eye view.

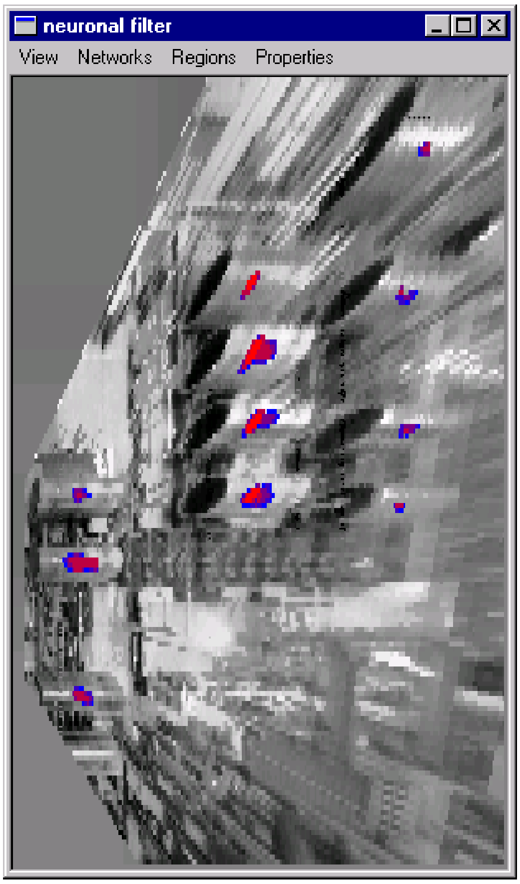

Figure 5: Object recognition in the scene: detected pipes are marked with a color code.

Beside the transformation this step performs a data reduction of about 85% by decreasing the spatial resolution of the image.
A high pass filtering is inserted into the processing chain to reduce the remaining differences in illumination of different parts in the scene.
The central recognition task is performed by neural filters. For each coordinate of the image the neural networks classify wether or not a pipe is actually present. To take into account the local characteristics, the image is divided into a raster of ‘responcebility regions’ with assigned perceptrons. The classification result for one of the images is depicted in fig. 5. The ‘degree of recognition’, i.e. the final output value of the perceptrons output layer, is represented by the color code: red for strong - blue for poor recognition and the unchanged black and white image for negative recognition.
In a last step the recognition results of the three neural filters are merged by the ‘pipe bundler’. For pipes of different diameters lying at the same physical position, the coordinates of their recognition-centers in the image are not identical. The position of a pipe in the physical coordinate system is calculated from the three different image coordinates of the recognition-centers.
Finally the resulting pipe positions and movements are reported to a logistic system which provides the signing roboter with this information.
The computational effort limits the temporal resolution of about 1/sec for the movement of (pipe) objects in the observed area.

NETWORKS AND TRAINING

Feed-forward networks of perceptrons [e.g. Müller/Reinhardt (1990)] are used for the recognition of pipes within the preprocessed images. The input to the first layer of the network are the gray values of a rectangular part of the image. The size of such a ‘feature window’ is chosen to be the minimum that covers all possible pipe dimensions.
The networks consists of a appropriate number of hidden layers and a single output perceptron. The output value classifies the contents of the feature window to be the image of a pipe or not.
The training data is collected from long time recordings by hand. The pipe examples and some random chosen no-pipe examples are used in a short initial training step. After the classification of the recorded images, additional examples are taken at the positions where errors have occurred. Itteratively, the network is trained, its performance is analyzed and it is re-trained with new examples until a sufficiently low error rate is reached.
The resulting network has a good overall classification performance. It serves as master network for the creation of specialized networks for the different parts of the image. Each of the specialized networks has to learn the characteristics of a specific region (background, light conditions, etc.). Starting with the master network as a ‘fist guess’, those networks are trained only with examples coming from their assigned ‘responsibility region’.
For the training a modified error backpropagation algorithm with a adaptive sigmoid function is used. The learning (strength) parameter and the size of the training set varies dynamically with respect to the actual training progress.

CONCLUSION AND OUTLOOK

We applied the technique of neural computing to a difficult real-world problem of image processing. A new image processing system was developed that works with excellent performance in an rough industrial environment:
failure rate below 5 (# unrecognized or lost objects / # tracked objects) for a prototype witch was put into operation in september ‘98.
This application shows the suitability of intelligent technologies to classification tasks under conditions where any conventional methods must fail.
For the future we plan to extend the concept to detect pipes, even when they are moved above the floor by a crane. For this purpose it seams to be necessary to use ‘intelligent’ light sources to reduce the influence of the disturbing light.

REFERENCES

Fecht, Nikolaus (ed.), 1999, “So gucken Sie nicht in die Röhre“, Flexible Automation 2-99.
Müller; Reinhardt, 1990,“Neural Networks“, Springer-Verlag, Berlin, Heidelberg.