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APPLICATION OF NEURAL NETWORKS TO THE ANALYSIS OF INDUSTRIAL IMAGES**

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This paper describes a system for automatic evaluation of digital images of a glass production process based on neural networks. Some details concerning used networks and learning sets are presented. The obtained results are compared with the description given by glasswork technology service. Also, some possibilities of improving the quality and the speed of the system are proposed.

1. Introduction

Although the literature concerning neural networks is very extensive, relatively few items concern their practical applications. Moreover, the majority of works referring to particular applications describe relatively simple problems, created artificially only to confirm the formulated theories. This might lead to the conclusion that taking the practical advantage of the possibilities given by the neural networks in particular applications is at least problematic. The aim of this paper is to show that such reasoning is erroneous, because it is possible to design the system, based on neural networks, which may be used for analysis of images generated in a particular technological process and simultaneously for the automatic evaluation of the state of this process.

2. Formulation of the Problem

Digital images of the process of window glass drawing by the Pittsburgh method were the starting material used for design and testing the system. They were recorded directly in the window glass works, by means of the computer system equipped with a camera and specialized image acquisition card we installed. The images were recorded with the resolution of 256×256 pixels, each of them of 16 gray levels. For explanation of the role the neural network plays it is necessary to give some information on the technology, to which it is to be applied.

In the process controlled, the sheet of steadily cooling down glass is drawn out vertically from the molten glass. During the process the sheet is passed through the system of asbestos rollers which are designed to support the panel, form its surface and reduce its thickness. After complete cooling the glass at the top of the hoisting

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machine, the sheet shifted continuously is cut into plates of the appropriate size. These plates are collected and stacked in the transporters.

The camera records a part of the drawn sheet (the total path passed by the sheet is of the order of a dozen meters). Basing on the recorded image either the correctness of the whole process is stated or possible disturbances are detected. More precisely, the bottom part of the formed glass sheet, adherent to the surface of the molten glass, is observed. The analysis is focused on the intermediate region between the liquid glass in the tank furnace and the semi-liquid bottom part of the formed sheet, the so-called "bulb". A typical image of this region, recorded during the normal process, is shown in Fig. 1. Some characteristic objects are visible in this Figure: parts of the asbestos rollers, edges of shields and the sheet itself, strictly its edge and the "bulb", together with the reflections of light sources, reflected in its concave meniscus. These sources of light are mainly the flames of gas burners, permanently heating the surface of molten glass outside the region in the observation field.

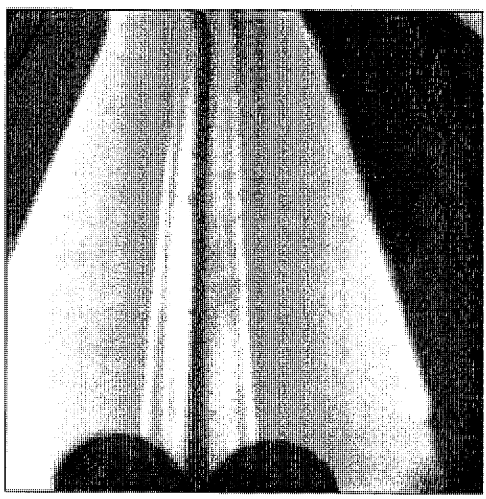

Fig. 1. A typical process — image HSO5.

Several disturbances may occur during the process. They may lead to the products of lower quality (defected fragments of the glass sheet) or even to the danger of breaking the process and a breakdown of the hoisting machine. The most common reason for these disturbances is the presence of the so-called stones in the molten glass. These are the pieces of the solid glass, which may cause damage to the asbestos rollers when they enter between them together with the glass sheet. They may also initiate cracking of the sheet, which may lead to breaking the drawn glass sheet and even to a serious breakdown of the hoisting machine.

Detection of stones visible on the surface makes no problem. Sometimes these stones are however completely covered with molten glass. In such cases the stone is not visible, but its presence may be concluded from the discontinuity in the external reflection of flames on the bulb. This situation will be later referred to as breaking of the bulb edge. The effects of the undetected bulb edge breaking are identical with those caused by the stone visible on the glass sheet surface.

The pictures presenting the described incorrect cases are shown below. Figure 2 shows the image recorded at the moment when a stone appeared in the observation field. Figure 3 shows the image recorded when a stone under the surface of the molten glass broke the bulb edge.

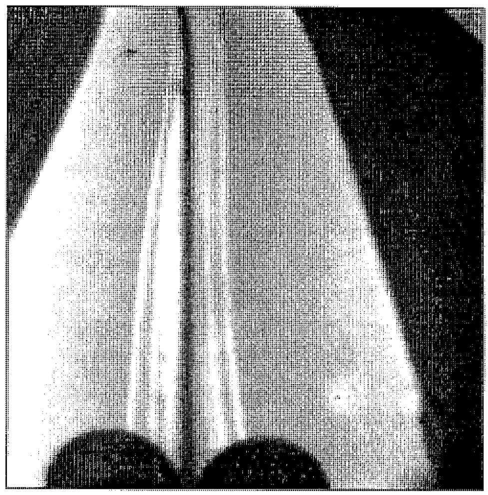

Fig. 2. The image of an incorrect process — stones.

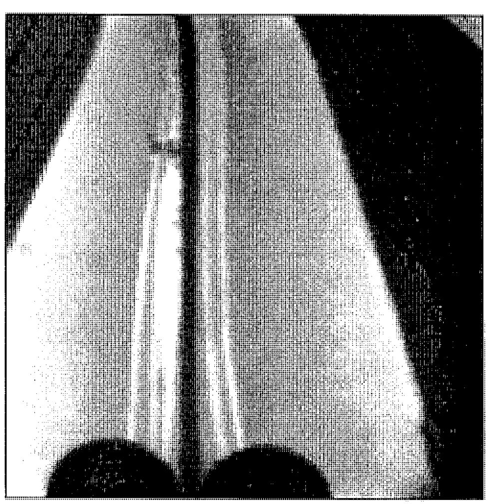

Fig. 3. The image of an incorrect process — breaking of the bulb edge.

Since the two basic types of process disturbances, illustrated in Fig. 2 and Fig. 3 represent 90–95% of all incorrect situations which may appear, detection of these situations was chosen as the basic goal at designing the system.

3. Methodology of Learning

The easiest way leading to the system automatically evaluating the state of the glass drawing process would be multiple presentation of acquired process images at the input of a designed neural network, together with the output information on the correctness of the process at the time of recording. Having taught the network "for a sufficiently long period of time", using one of the algorithms of learning (e.g. back-propagation) we have a non-zero chance that after completing the learning session the network would be able to evaluate the image and give its opinion on the state of the process. Practical realization of this approach may, however, create many problems.

As the dimensions of the input image are relatively big, the evaluating network should have 256×256 neurons in the input layer (not to mention the hidden and output layers). Very few programs modelling neural networks are able to create such a big network. Moreover, even if that occurred to be possible, the time needed for learning such large network would be very long. Low speed and high cost of operation (resulting from the hardware requirements) raise also doubts about the possibilities and purposefulness of such an approach. Moreover, for such a large network a very long learning set must have been acquired (of order of several thousands of images), which would require a very large system memory. Finally, it may appear that the network recognizes images from the learning set correctly, while it is not able to evaluate properly the images contained in the test set, because its ability to generalize is not known *a priori*.

The above-mentioned reasons lead to the acceptance of a new strategy of learning we proposed, namely the mixed strategy of learning. It seems reasonable to replace the processing of the whole image in one network by introduction of the mechanism enabling local recognition of the parts of images by small networks (of a small number of elements in the input layer), focusing the attention on the important details. Introduction of small networks makes also possible a replacement of the large learning set, composed of the whole images, with a more economical set of the fragments, containing generated elements and corresponding to the patterns for the breakdown situation considered.

This approach has the following advantages over the approaches discussed earlier:

- considerable reduction of the network dimensions;
- limitation of the analysis to the places in which disturbances may appear, which leads to an increase in the system sensibility, quality of recognition and simultaneous elimination of erroneous recognitions;
- speeding up the learning process;
- reduction of the network sensibility to image fluctuations (for instance due to differences in illumination and small shifts or curvatures of the image);
- shortening the learning set.

4. Structure of the Network

The neural networks of the back-propagation type, traditionally most commonly used in recognition of images, were used for the analysis of the presented images. As the images of both kinds of possible perturbations differ substantially, we decided to recognize them separately. Thus, the task of recognition of the incorrect situations was split into two partial ones:

- detection of stones,
- detection of discontinuities in bulk edges.

Each of the above problems required different structure of the network. Nevertheless, in both cases the local processing using small networks was chosen. The role of these networks was scanning the images in search of fragments close to the patterns used during the process of learning and corresponding to the breakdown situations.

The detailed description of the applied networks needs separate description of the problem of stones detection and recognition of breaks in bulb edges.

4.1. Detection of Stones

The problem of stones detection was easier to solve because it required only finding the presence of the characteristic objects (stones) in the image, of *a priori* known (roughly) dimensions and shape. For this reason, a network of 8×8 neurons in the input layer, without the hidden layer appeared to be sufficient in this case. This network responded with the signal close to 1 in the case of a stone detection, while it generated the signal close to zero in all other cases. The stone detecting system gave to the input of this network all the fragments of the image, of dimension 8×8, for checking the eventual presence of the stones. The response exceeding the value of 0.8 was accepted as the signal of breakdown.

4.2. Detection of Breaks in the Bulb Edge

The problem of breaks detection appeared to be more difficult because there was a need of prior separation of the bulb edges. In this case the problem was not limited to detection of the presence of some pattern (a break). The fact that the occurrence of the pattern could appear only in definite places, not in any arbitrarily chosen fragment of the image, had to be taken into account. The outer edges of the bulb had to be separated at the beginning, because only the break of those edges means the breakdown situation. In this case the image processing by means of the Laplace transform, leading to edges separation, was necessary. The fragments of such processed image were passed to the neural network, similar to this one detecting the stones. The only difference lies in the dimensions of the input layer, reaching in this case 8×32 neurons. The difficulties in teaching one network the detection of disturbances on both outer glass sheet edges (left and right) caused the necessity of creating two networks (of the same structure) and teaching them with two separate learning sets. The effect of the action of these networks for all possible fragments of the input image were pictures showing only the outer edge of the bulb (the left or the right one, depending on the form of the learning set) and the edge of the visible fragments of the shields.

The images obtained in such a way were the input images for the consecutive network (strictly, two networks, for the left and right edge, respectively), of identical structure, but taught with different learning sets. Its role was to detect likely breaks in the edges. The structure and operation of this network were analogous to the previous one, except for the dimension of the input layer, equal to 24×4 neurons. The appearance of the response exceeding 0.9 on the network output signalled the probability of the edge break in the presented fragment of the image. The structure of the network used for local processing is shown in Fig. 4.

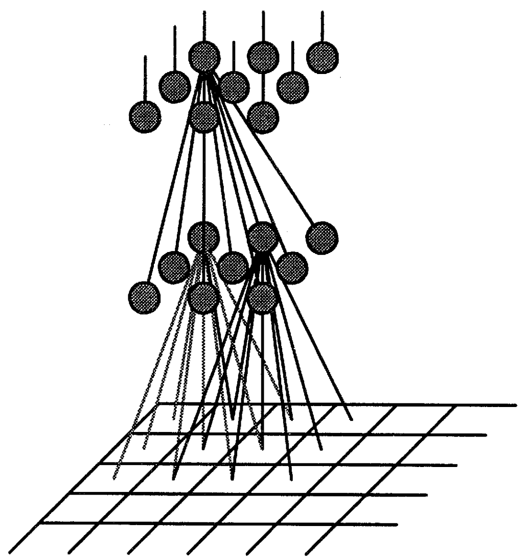

Fig. 4. Example of the local processing neural network. Connections between two neurons of the first net and one neuron of the second net are presented.

5. The Learning Sets

As mentioned earlier, the learning sets used for the networks presented above were not collections of fragments of the images processed, but they were generated. Thus, the number of elements in these sets was considerably reduced, which led to a significant reduction of the learning time (it is well-known that the time of learning is one of the disadvantages of the back-propagation networks). The presentation of the generalized patterns of breakdown situation was the main goal of the generation of the learning sets.

Detection of stones was easier both because of the less complex structure and the simpler representation of the breakdown situation. In the applied learning set there were two "pictures" of stones differing in size (the expected response equal to 1) and patterns of the normal situations (the response equal to 0). The "pictures" of sheet edges and rollers and the background were the patterns of normal situations. Moreover, the necessity of adding a pattern resembling a stone, but of high level of grayness, appeared. This pattern occurred sometimes in the analysed images of the normal bulb, causing the erroneous signal of the breakdown situation. The patterns applied in learning, are shown in Fig. 5 in the form of numerical matrices.

.69 .69 .69 .56 .56 .69 .69 .69	.69 .69 .69 .69 .69 .69 .69 .69	.81 .88 .88 .94 .94 .88 .88 .81
.69 .69 .56 .50 .50 .56 .69 .69	.69 .69 .69 .50 .50 .69 .69 .69	.88 .88 .88 .94 .94 .88 .88 .88
.69 .56 .50 .44 .44 .50 .56 .69	.69 .69 .50 .44 .44 .50 .69 .69	.88 .88 .81 .75 .75 .81 .88 .88
.56 .50 .44 .38 .38 .44 .50 .56	.69 .50 .44 .38 .38 .44 .50 .69	.25 .25 .25 .25 .25 .25 .25 .25
.56 .50 .44 .38 .38 .44 .50 .56	.69 .50 .44 .38 .38 .44 .50 .69	.25 .25 .25 .25 .25 .25 .25 .25
.69 .56 .50 .44 .44 .50 .56 .69	.69 .69 .50 .44 .44 .50 .69 .69	.25 .25 .25 .25 .25 .25 .25 .25
.69 .69 .56 .50 .50 .56 .69 .69	.69 .69 .69 .50 .50 .69 .69 .69	.25 .25 .25 .25 .25 .25 .25 .25
.69 .69 .69 .56 .56 .69 .69 .69	.69 .69 .69 .69 .69 .69 .69 .69	.25 .25 .25 .25 .25 .25 .25 .25
.81 .81 .81 .63 .63 .81 .81 .81	.81 .63 .31 .31 .31 .31 .63 .81	.63 .38 .38 .31 .31 .31 .31 .31
.81 .81 .63 .63 .63 .63 .81 .81	.81 .63 .31 .31 .31 .31 .63 .81	.63 .38 .38 .31 .31 .31 .31 .31
.81 .63 .63 .63 .63 .63 .63 .81	.81 .63 .31 .31 .31 .31 .63 .81	.63 .38 .38 .31 .31 .31 .31 .31
.63 .63 .63 .63 .63 .63 .63 .63	.81 .63 .31 .31 .31 .31 .63 .81	.88 .63 .38 .38 .31 .31 .31 .31
.63 .63 .63 .63 .63 .63 .63 .63	.81 .63 .31 .31 .31 .31 .63 .81	.88 .63 .38 .38 .31 .31 .31 .31
.81 .63 .63 .63 .63 .63 .63 .81	.81 .63 .31 .31 .31 .31 .63 .81	.88 .88 .63 .38 .38 .31 .31 .31
.81 .81 .63 .63 .63 .63 .81 .81	.81 .63 .31 .31 .31 .31 .63 .81	.88 .88 .63 .38 .38 .31 .31 .31
.81 .81 .81 .63 .63 .81 .81 .81	.81 .63 .31 .31 .31 .31 .63 .81	.88 .88 .63 .38 .38 .31 .31 .31
.31 .31 .31 .31 .31 .31 .38 .38	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .31 .31 .31 .38 .63	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .31 .31 .31 .38 .63	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .31 .31 .38 .63 .88	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .31 .31 .38 .63 .88	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .31 .38 .63 .88 .88	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .31 .38 .63 .88 .88	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81
.31 .31 .31 .38 .63 .63 .88 .88	.06 .06 .06 .06 .06 .06 .06 .06	.81 .81 .81 .81 .81 .81 .81 .81

Fig. 5. The patterns used for detecting stones.

In the case of detecting the edge breaks, the left and right edges should have been treated separately. Moreover, the situation was complicated by the necessity of prior separation of the bulb edges. Due to the limited length of this work only one learning set, used for the network scanning the left edge will be presented in detail. The elements of the learning set for the other network (searching the right edge) were mirror reflections of the presented set.

The element representing the left edge was a "picture" of the vertical line, slightly inclined to the right, located in the right border of the image (the expected network response for this object equal to 1). This element represented the lines, with no objects on their left side (being really the left edge). In order to eliminate the other edges, the patterns containing this element with the second line added on the left side were generated (the expected response equal to 0). The number of these patterns was determined by the number of all the locations of the given line. Moreover, the pattern protecting against too strong influence of the vertical line (appearing initially due to the relatively high values of the image pixels in this place) was added to the learning set. Thus, the structure of the images learning the network had the form given in Fig. 6.

The learning set for the network detecting the left edge breaks was composed of a few "pictures" of the break, differing in their width (the required network response equal to 1.0) and of the images of the continuous sloped edge line (the required response equal to 0.0). These patterns are presented in Fig. 7 in the form identical with that one for the patterns for detecting the stones.

.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02

.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02
.02	.08	.08	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.10	.10	.02	.02	.02	.02	.02	.02

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.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.08	.08	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.08	.08	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.08	.08	.02	.10	.10	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.08	.08	.10	.10	.02	.02	.02	.02	.02	.02
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.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.08	.08	.10	.10	.02	.02	.02	.02	.02	.02
.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.08	.08	.10	.10	.02	.02	.02	.02	.02	.02

Fig. 6. The examples of the patterns used for detecting the left bulb edge.

.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .99 .99	.01 .01 .99 .99	.01 .01 .01 .01	.01 .01 .99 .99	.02 .02 .02 .02
.01 .01 .01 .01	.01 .01 .01 .01	.01 .01 .01 .01	.01 .99 .99 .01	.02 .02 .02 .02
.01 .01 .01 .01	.01 .01 .01 .01	.01 .01 .01 .01	.01 .99 .99 .01	.02 .02 .02 .02
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.99 .99 .01 .01	.01 .01 .01 .01	.99 .99 .01 .01	.99 .99 .01 .01	.02 .02 .02 .02
.99 .99 .01 .01	.01 .01 .01 .01	.99 .99 .01 .01	.99 .99 .01 .01	.02 .02 .02 .02
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.99 .99 .01 .01	.01 .01 .01 .01	.99 .99 .01 .01	.99 .99 .01 .01	.02 .02 .02 .02
.99 .99 .01 .01	.01 .01 .01 .01	.99 .99 .01 .01	.99 .99 .01 .01	.02 .02 .02 .02

Fig. 7. The examples of the patterns used for detection of the edge breaks.

6. Results

To realize the formulated task a neuroprocessor card BALBOA, based on the processor Intel 80860, was used. This card was connected with the frame-grabber DT2862, produced by Data Translation. The functioning of the network was tested on thirteen images (twelve of them are presented in Fig. 8), recorded in the glass works and interpreted in details by the experts from the glass works. The results obtained are presented in Table 1.

Tab. 1. Results of the system analysis.

Item	Name of the image	Diagnosis of the technology engineer	Diagnosis of the system
1	HSO1	Bulk edges slightly curved	Without claims
2	HSO3	Top right — a stone, below a break of the bulb line	Stones were detected
3	HSO4	Normal situation	Without claims
4	HSO5	Normal situation	Without claims
5	HSO6	From the right side a stone entered (in the middle)	Without claims
6	HSO8	From the left side a stone is entering (at the top)	Stones and breaks of the left edge detected
7	HSO9	Left top — a stone, below the other one enters a bulb	Stones were detected
8	HSO10	Similarly as above, the stone shifted to the left, the second one entered the sheet	Stones were detected
9	HSO11	As above, next two stones appeared on the left	Stones and breaks of the right edge detected
10	HSO12	AS above, a moment later	Stones and breaks of the left edge detected
11	HSO13	Continuation of the previous situation	Stones were detected
12	HSO14	As above	Stones were detected
13	HSO15	The observed stones enter the bulb	Stones and breaks of the left edge detected

The comparison of the results obtained with the expertise shows that in the majority of cases the system gave the proper diagnosis. The erroneous diagnosis was found only in the case of the image HSO6. This was caused by the specific shape of the left sheet edge break. Moreover, in the case of images HSO11 and HSO14 the network not only found the real situation but also misinterpreted some fragments of the image as similar to a stone and erroneously signalled the stone in the sheet.

Signalling the sheet edge breaks does not necessarily mean the appearance of a real break. This is caused by two stage detection of the breaks, described in Section 4. In all cases of stones located in the neighbourhood of the sheet edge, the first stage of detection led to the edges with breaks. These breaks were signalled in the second stage of detection. So, detection of such a "false" break was not exactly a mistake but it was rather a side effect of the appearance of stones.

7. Conclusions

The results presented above prove that the application of neural networks is not limited to simple cases. They may be used for creation of the system of the automatic state evaluation of a technological process, basing on its digital image, in such a big and complex system as the hoisting machine in glass works. The results of the system operation are consistent with the expertise, although they were obtained basing on a

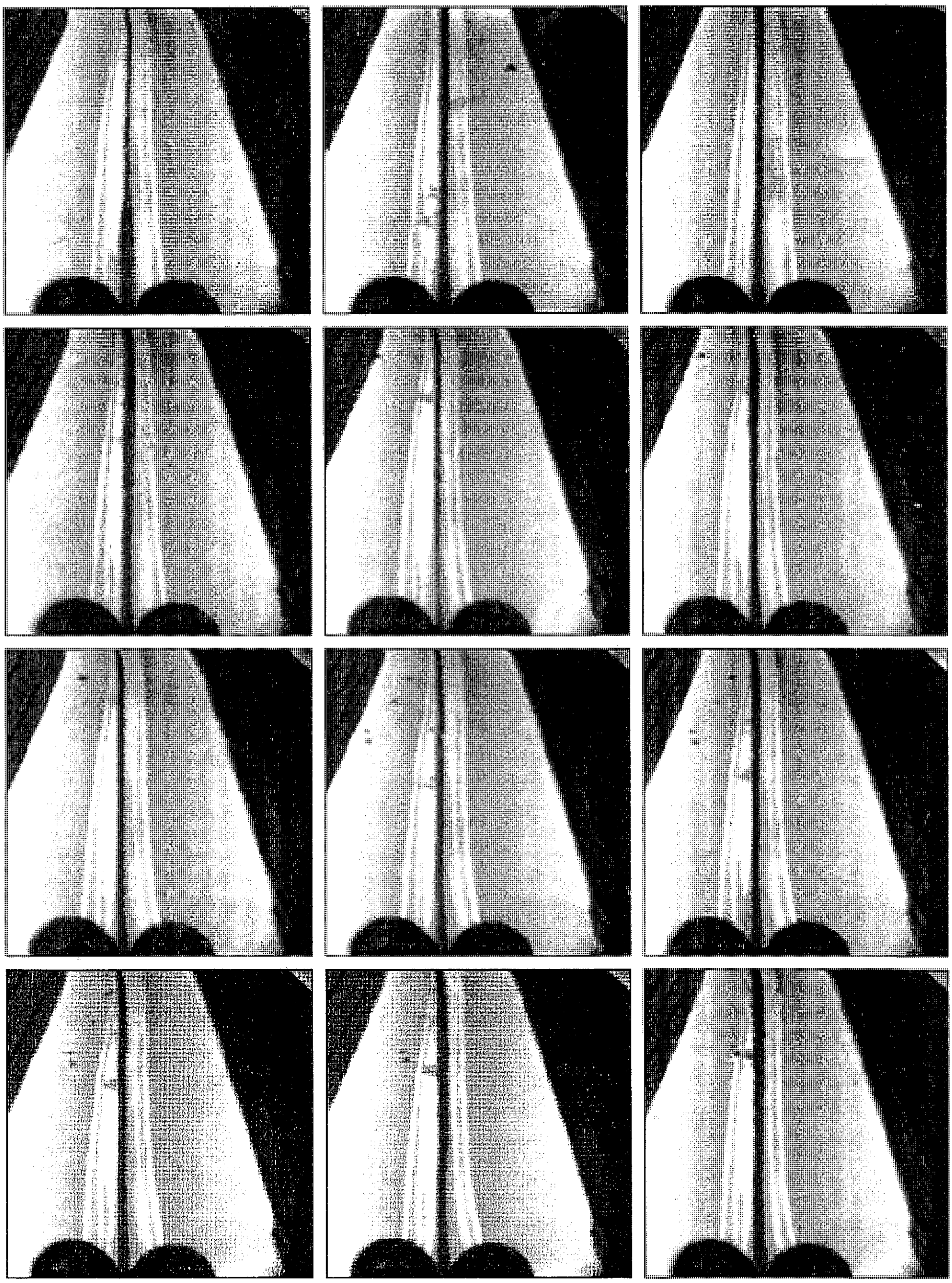

Fig. 8. The analysed images (from the top to the bottom: HSO1, HSO3, HSO4, HSO5, HSO6, HSO8, HSO9, HSO10, HSO11, HSO12, HSO13).

small set of simple patterns for the breakdown situations. It may be expected that the extension of the learning set to new patterns will improve the reliability of the system and the quality of diagnosis as well as it will make possible recognition of the breakdown situations different from those shown in this paper. Also the limitation of the analysis to these image fragments where the disturbances may appear seems reasonable. This would affect both the quality of the work of this system and the speed of analysis, thus making the *on-line* evaluation of the process possible.

References

Grossberg S. (1988): *Neural Networks and Natural Intelligence.* — Cambridge, Mass.: MIT Press.

Maren A., Harston C.T. and Pap R.M. (1990): *Handbook of Neural Computing Applications.* — New York: Academic Press, Inc.

Tadeusiewicz R. (1991): *Neural networks - a survey.* — Electronics, No 2, (in Polish).

Tadeusiewicz R. (1993): *Neural Networks.* — Warsaw: Academic Publishing House, (in Polish).