Automatic recognition of drill condition on the basis of images of drilled holes

Michal Kruk
Faculty of Applied Informatics and Mathematics
Warsaw University of Life Sciences, Warsaw, Poland
MICHAL_KRUK@SGGW.PL

Albina Jegorowa
Faculty of Wood Technology
Warsaw University of Life Sciences, Warsaw, Poland

Jaroslaw Kurek
Faculty of Applied Informatics and Mathematics
Warsaw University of Life Sciences, Warsaw, Poland

Stanislaw Osowski
Institute of Theory of Electrical Engineering, Measurement and Information Systems
Warsaw University of Technology and Military University of Technology, Warsaw, Poland

Jaroslaw Gorski
Faculty of Wood Technology
Warsaw University of Life Sciences, Warsaw, Poland

***Abstract*—This paper presents an automatic algorithm to recognize the condition of drills on the basis of analysis of the drilling hole images. The algorithm includes the image preprocessing leading to extraction of the diagnostic features, which are used as the input attributes for the classification system. The condition of drill is classified into two groups: the useful one (the sharp enough state) and worn out (useless in production).**

***Keywords*—image processing, drills, classification**

I. Introduction

To achieve higher quality and productivity of machine tools the cutting process diagnostic systems especially TCM (Tool Condition Monitoring) [1,2,3] and PCM (Process Condition Monitoring) are used. The fundamentals of these techniques applying many sensors installed in the production line have been described in the papers [1,2]. However, TCM and PCM are very expensive. Authors of this paper consider the cheaper method of assessing the condition of drill based on actual image of the hole made by the drill.

The paper presents an automatic approach to the recognition of the drill condition in a standard laminated chipboard drilling process on the basis of image of hole. The condition of the drill, which is connected with the shape of hole was classified into two classes: "useful" (sharp enough, circumference of the hole is not disturbed) and "useless" (worn out, blunt). In the case of "useless" drill the shape of the hole is not acceptable from the point of view of furniture producers.

II. Materials

Materials used in experiments were prepared in the Faculty of Wood Technology, Warsaw University of Life Sciences in the form of images of 450 holes made by the new drills and drills of worsening quality. In each case two images have been registered: one on the input side of material (so called input hole) and the second on the output side (the output hole). It means 900 images used in further processing. The examples of such images are shown in Figure 1.

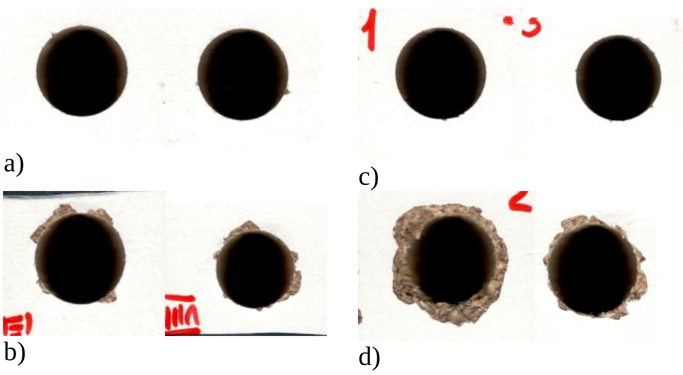

Fig. 1. a) Input holes drilled by undamaged drill, b) input holes drilled by warned out drill, c) output holes drilled by undamaged drill, d) output holes drilled by worned out drill.

It is easy to observe that the holes made by damaged drill have destroyed edges and surface - they are unacceptable in furniture production in wood industry.

All data used in experiments were obtained using standard Buselatto JET 100 CNC vertical machining centre. The drilling process was performed on the laminated chipboard using standard drills of the 12 mm diameter with tungsten carbide tips ("FABA" - Poland). The typical pictures of chosen chipboard and drill are depicted in Fig. 2.

The database for the numerical experiments was prepared by using 5 drills. In the first phase all new drills were used in laminated chipboard drilling process.

Fig. 2. The image of a) laminated chipboard, b) drill used in experiments.

The next phases the production process were continued using the blunted drills. In each step drill was blunted more and more. After each blunting 10 holes were drilled. It resulted in 5 (drills) x 10 (holes) x 9 (blunting process) x 2 (input and output holes) = 900 holes. Each hole in laminated chipboard was scanned and cropped. In this way, 900 images were obtained. They represented 9 classes of degree of drill damage.

III. IMAGE PREPROCESSING

The first step was image processing. The most important task in this step was image binarization which could depict the hole and damaged surface but hide other imperfections of laminated chipboard. The most popular Otsu [4,5] method gave unacceptable results. The method using the combination of thresholding with one value of threshold and adaptive approach to threshold was good enough and gave the satisfactory results. The algorithm allowed to separate the foreground from the background at non-uniform illumination. The experiments were performed in Matlab [6] environment.
The used adaptive thresholding may be presented in the form of the following algorithm:

- conversion the image from RGB to grayscale,
- filtering of the grayscale image using the average filter with window size equals 50x50,
- forming the differential image through subtracting the filtered image by the original grayscale image and some chosen threshold t, where t was subject to adaptation. In our case the best results were obtained for t=0.07,
- computing the complement of the image.

The first step after filtering was image binarization with low value of threshold (25). The second step was image binarization by adaptive thresholding. The next step was adding the results of previous two steps. The whole process is depicted in Figure 3.

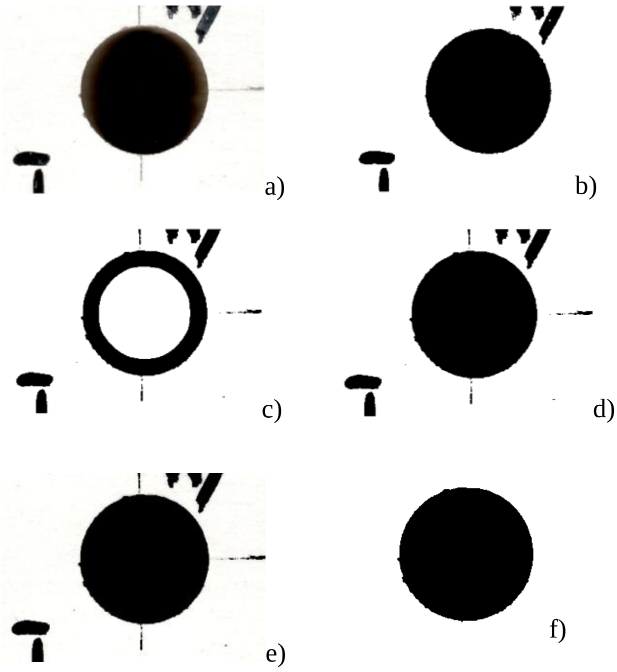

Fig. 3. The illustration of the following steps of preprocessing in creation the final image of the hole: a) input image, b) binarized image after one value of threshold, c) image after adaptive thresholding, d) superposition of images after b and c steps, e) combination of original image and result of step c, f) final binarized result.

The adaptive thresholding was found better in recognition of the distorted edges of the holes. However this method does not fill the inner space of the hole. To compensate for this the combination of one value and adaptive thresholding was used. Final image used in further processing is the object with the largest area.

IV. FEATURES EXTRACTION

Automatic performance of the diagnostic system requires to generate the numerical descriptors, which will serve as the input attributes to the classifier. In industrial process very important factor taken into account in the manual assessment of the drilled holes is based on the difference between the maximum diameter of the hole and the diameter of the drill. It may be described by the following equation

$$A = \frac{D_{MAX} - D}{2}$$

where D_{MAX} is the maximum diameter of the hole and D - diameter of the drill. The interpretation of these values are presented in Fig 4. In our case the value of D is constant and it is always equal 12 mm irrespective of the blunting process (the blunting does not change the diameter of drill)..

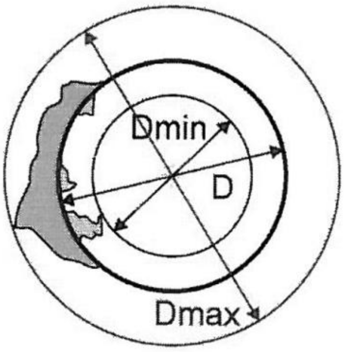

Fig. 4. Interpretation of diameters used in generating numerical features.

To generate more numerical descriptors we take into account the other factors characterizing the regularity and smoothness of the circumference of the hole. Such descriptors use the minimum radius enclosing circle and maximum radius of the described circle. Let us denote them by D_{max} and D_{min} Their interpretation is given in Fig 5.

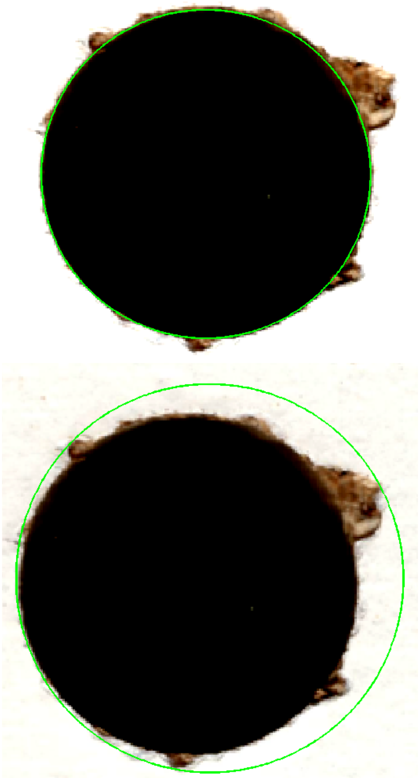

Fig. 5. Maximum inscribed (top) and minimum described (bottom) circles.

As a results of such preprocessing steps the following eight diagnostic features have been defined and used as the input attributes to the classification system.

- Radius of the inscribed circle
- Radius of the described circle
- Area of the hole
- Convex area
- Perimeter of the hole
- Major axis length
- Minor axis length
- Solidity factor

As a result all 900 images representing input (450) and output (450) holes have been described by 8 diagnostic features. Each image was associated with the appropriate class: one of 9 classes defining different stages of blunting.

V. ANALYSIS OF CLASS SIMILARITY

The classification task was performed using the support vector machine classifiers (SVM) of the Gaussian kernel [7]. The recognition of 9 classes, very similar to their neighbors was a very difficult task. This is due to the variety of shapes obtained in the real production following from some differences in chipboard material. Sometimes the images belonging to the same class are totally different. The obtained accuracy of recognition of 9 classes was poor. The average recognition rate obtained in 10-fold cross validation approach was 40% for input holes and 34% for output holes.

Therefore, in the next experiments we have decided to group the data into 2 classes only: the sharp enough (class 1) and useless from production point of view (class 2). The additional task to solve is to join classes which are similar to each other. To solve the problem k-means algorithm performed on the whole set of features was applied. The result of k-means in the form of dendrogram is depicted in Fig 6.

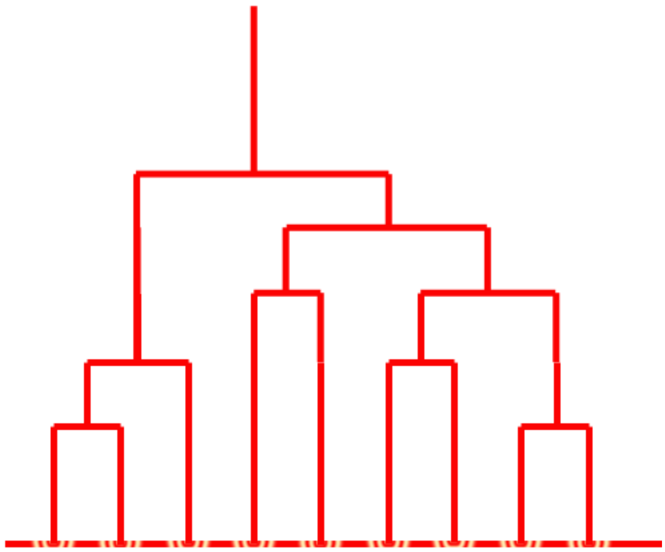

Fig. 6. The dendrogram representing the similarity of classes.

It is easy to observe that classes 1,2 and 3 were closest to each other. Similar process has combined together the classes from 4 to 9. On the basis of this result we decided to group all classes into two sets. The first set contained classes from 1 to 3 and the second one contained classes from 4 to 9. It means that first class may be treated as representative of a sharp enough drill and the second one as a useless drill.

VI. RESULT OF NUMERICAL EXPERIMENTS

To perform final classification process two types of classifiers: kNN and SVM [7] were used. They were combined with three different types of features selection: Fisher method, correlation feature selection (CFS) and fast correlation based filter (FCBF) [8]. The results of validation performed in 10-fold cross validation approach on half of the data representing the input holes (the other half was concerning the output holes) are given in Tables 1 to 4. In the performed experiments the following parameters have been used:

- kNN - k=3
- SVM, Gaussian kernel, C=800, gamma=0.3
- Fisher selection method: the best results were obtained for only 2 features (radius of described circle and the solidity factor)

Table I presents the results of estimation of the sharpness of the drill based on the shape of the input holes. They refer to the average accuracy of both classes recognition.

TABLE I. ACCURACY OF CLASS RECOGNITION FOR INPUT HOLES

Classifier	**Features Selection Method**			
	All	***Fisher***	***FCBF***	***CFS***
kNN	88.38%	90.01%	90.17%	91.06%
SVM	93.78%	91.07%	91.07%	91.07%

Table II presents the confusion matrix for this case. The first row represents the samples of class 1 and the second row the class 2. The accuracy of estimation of class 1 was equal 91.7% and this value for the class 2 was 94.8%.

TABLE II. CONFUSION MATRIX FOR THE BEST RESULT

133	12
16	289

Table III and IV depict results concerning the recognition of the sharpness of drill on the basis the output holes. The accuracy of class recognition is similar to the previous case from the statistical point of view.

TABLE III. ACCURACY OF CLASS RECOGNITION FOR OUTPUT HOLES

Classifier	**Features Selection Method**			
	All	***Fisher***	***FCBF***	***CFS***
kNN	92.85%	92.85%	92.85%	92.85%
SVM	94.66%	91.96%	89.28%	88.39%

Table IV shows a bit better results of recognition of class one. The accuracy in this case has increased from 91.7% (in the case of input holes) to 92.7%. The same situation is true also for class 2 (the increase from 94.8% to 95.8%).

TABLE IV. CONFUSION MATRIX FOR THE BEST RESULT

153	12
12	273

The interesting fact is that the best results are obtained in both cases for the whole set of diagnostic features (without reduction of any descriptor). The SVM classifier in most cases was superior to kNN.

VII. CONCLUSIONS

The paper proposed the simplified method of assessing the condition of drill in chipboard drilling process. The described procedure is based on the analysis of the shape of the holes made by the actual drill. Thanks to such simplification the diagnostic stage is very simple and does not need the expensive arrangement of measurement devices. Moreover, it can be easily adapted in any wood factory without expensive rearrangement of the production devices. However, further research is needed to increase the accuracy of diagnostic system.

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