Evaluation of the State of Cutting Tools According to Its Texture Using LOSIB and LBP Variants

Oscar García-Olalla, Laura Fernández-Robles, Eduardo Fidalgo, Víctor González-Castro and Enrique Alegre

Abstract The FRESVIDA project deals with the life assessment of cutting tools working under severe conditions using digital image processing techniques. The description of texture in materials through artificial vision techniques is very useful for this goal. There are several works based on Local Binary Patterns (LBP) and many variants such as Local Binary Pattern Variance (LBPV) or Diamond-LBP Code (DLBPCS) that have proved to be effective when distinguishing materials according to their texture. The Outex dataset comprises images from 24 materials acquired under different illumination conditions, becoming the present reference dataset for texture evaluation. In this work, several descriptors have been extracted based on the LBP from the Outex dataset, as well as their combination with LOSIB (Local Oriented Statistical Information Booster). All of them have been classified with Support Vector Machine (SVM) to assess which one is more useful for the above-mentioned task. In this case, all descriptors achieve a lower performance level combined with LOSIB because Outex is a data set that studies rotation invariances.

Keywords Texture · Computer vision · Cutting tools · Local binary pattern

1 Introduction

The development of control techniques for the detection of tool wear in machining processes is a key factor in automated production systems. Tool Condition Monitoring Systems (TCMS) drastically reduce manufacturing costs. On the one

O. García-Olalla (✉) · L. Fernández-Robles (✉) · E. Fidalgo · E. Alegre
University of León, Campus de Vegazana S/N, 24071 León, Spain
e-mail: ogaro@unileon.es

L. Fernández-Robles
e-mail: lferr@unileon.es

V. González-Castro
University of Edinburgh, Edinburgh, UK

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hand, TCMS decrease the amount of time used by an operator to make an inspection. On the other hand, they help to avoid breakdowns that are sometimes undetectable by a worker. In the last years, the search of techniques for automated tool wear estimation has become very relevant due to the birth of high-speed machinery, which causes a significant reduction of the life cycle of the cutting tools.

The University of León is participating in the FRESVIDA research project, funded by the Spanish Government, which aims at developing a system capable to determine the life cycle of milling cutting tools by means of a fusion of acoustic signals, vibrations and visual information of the worn areas. This project arises as an answer for the industrial necessity of TECOI, a company specialised on the production of tool machines. Figure 1 shows two examples of milling head tools that contain cutting tools, also called inserts. On the right, the head tool that is used in this project is shown.

Weckenmann and Nalbantic (2003) demonstrated that the cost of changing cutting tools can sum up to a twelve per cent of the total production cost. For this reason, there is a high economic interest on the improvement of the efficiency of the tool monitoring systems (Kopac 1998). Furthermore, it has been established that around a 20% of the non-productive time in modern manufacturing systems is due to cutting tools failures (Kurada and Bradley 1997).

For all these reasons, tool wear monitoring in real time has become an active research field that aims at eliminating the subjectivity of the operators while using objective criteria to predict the appropriate time to replace a cutting tool. Lim (1995) concluded that the use of sensors to estimate the ideal moment of cutting tool replacement would reduce up to a 40% the production costs. Based on this theory, several works have emerged in the last years such as the ones by Painuli et al. (2014), Wang et al. (2014) or Fernández-Abia et al. (2014).

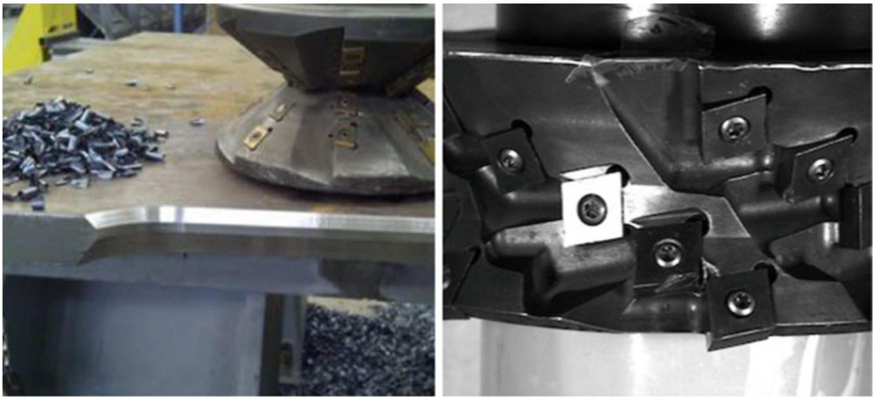

Fig. 1 On the *left*, an example of a milling head tool. On the *right*, the milling head tool model employed in this project

In this context, the use of artificial vision and, more precisely, texture analysis becomes very interesting. It allows for the development of a precise and efficient system that determines the state of the tool in real time without the effect of usual problems like noise, which may affect the force sensors, vibrations, etc. Several researchers have studied artificial vision techniques to determine the state of cutting tools (Alegre et al. 2008). They are based on different approaches such as the Wavelet transform (Morala-Argüello et al. 2012), Laws descriptors (Alegre et al. 2012), contour signatures (Alegre et al. 2009) or descriptors based on moments (Barreiro et al. 2008).

Texture analysis is an intricate problem on the field of artificial vision, whose purpose is the description of the spatial variability of an image considering the intensity level of its pixels.

In the last years, several research fields have used approaches based on texture analysis to automate processes. For example, in the biological field, García-Olalla et al. (2015) proposed a system based on a combination of Local Binary Pattern (LBP) (Ojala et al. 1994) information extracted from the Wavelet transform and Fourier moments in order to determine the integrity of the acrosome of boar spermatozoa, yielding a hit rate higher than 99%. González-Castro et al. (2012) proposed a method that classifies texture by means of descriptors based on adaptive Mathematical Morphology without a priori knowledge about the texture.

The LBP is becoming one of the most popular techniques due to its simplicity and high discriminant power. Many research groups are working on creating algorithms based on LBP (García-Olalla et al. 2013). Guo and its research group have performed several modifications of LBP like Adaptive LBP (ALBP) (Guo et al. 2010a, b, c), Completed LBP (CLBP) (Guo et al. 2010a, b, c) or LBP Variance (LBPV) (Guo et al. 2010a, b, c). In the industrial environment, Tajeripour et al. (2007) proposed a modification of LBP to detect defects on manufacturing processes, achieving results with a hit rate higher than 95%.

One of the most widely used datasets in the study of the behaviour of texture descriptors is Outex. Outex was developed by Ojala et al. (2002a, b) and currently it is still a reference dataset for the evaluation of new descriptors. For this reason, many researchers have used these images to verify their works. Ojala et al. (2002a, b) used this dataset to verify the good use of uniform LBP. Other examples of works that use Outex are: Ahonen et al. (2009) or more recently Yuan (2014) or Zand et al. (2015).

The objective of this paper is to carry out a study of different texture description methods based on LBP using the Outex dataset. In this way, possible useful descriptors can be determined in the application field of the FRESVIDA project, which is focused on the tool wear estimation in milling machines.

The rest of the paper is organized as follows: in Sect. 2 the different types of evaluated descriptors are explained. The experiments, the dataset and the obtained results are shown in Sect. 3. Finally, conclusions are drawn in Sect. 4.

2 Methodology

2.1 Software Engineering

In order to carry out this project, a software engineering method based on iterative and incremental development known as "Agile development" has been chosen. This scheme eases the development of the project by means of collaboration between self-organizing groups and communication between team members and clients. This development method is based on delivering periodically a usable software solution to the customer. For each delivery, the customer carries out an analysis of the delivered prototype and makes a list of priorities that must be accomplished in the next deliverable. In this case, a 1-week period between each delivery was used because of the fluent communication existing among the artificial vision and machining groups.

This type of development simplifies the programmers' work because the objectives to be accomplished are very specific. Moreover, due to the good and periodic communication between the programmers and the machining experts group, mistakes due to the lack of knowledge of the software development group could be solved easily without causing a bad implementation that leads to a non-optimal solution or to delays in the project schedule.

2.2 LBP

The Local Binary Pattern (LBP) (Ojala et al. 1994) is a simple but effective texture operator that labels each pixel of an image with a binary value using a threshold based on its neighborhood.

Due to its low computational cost and high discriminative power, LBP has become one of the most used methods in applications related with texture analysis. The most important advantage of LBP in real applications is its robustness against changes in the gray level intensity, caused by differences in illumination, among other things.

The LBP is calculated on grayscale images by means of Eq. (1), where P is the number of pixels taken into account in the neighborhood, R is the neighborhood size and g_c and g_p are the gray level values of the central pixel and each of the p pixels of the neighborhood respectively.

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(g_p - g_c)2^p, \quad s(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases} \tag{1}$$

In Fig. 2, the process is shown graphically.

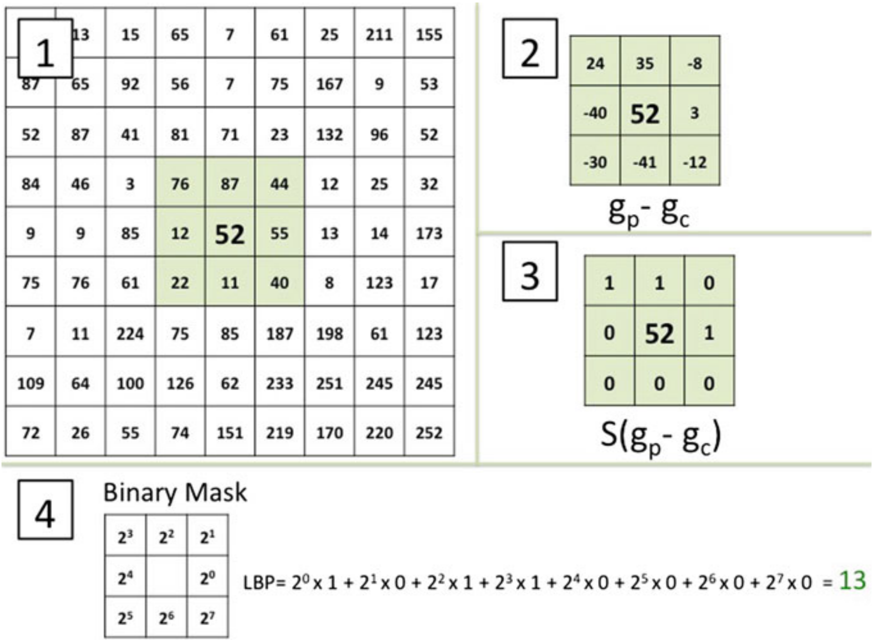

Fig. 2 Visual example of the extraction process of the corresponding value to LBP for a specific pixel

2.3 ALBP

Guo (2010a) proposed a new texture descriptor based on LBP, which is focused in obtaining information not extracted in the original method. In this case, the method was focused in adding information of the texture orientation. The method minimizes the average variations and the standard deviation of the directional differences. Therefore, it was proposed to add an extra parameter w in the Equation $|g_c - w_p * g_p|$. The objective function is defined in Eq. (2).

$$w_p = \arg_w \min\left\{\sum_{i=1}^{N}\sum_{j=1}^{M} |g_c(i,j) - w \cdot g_p(i,j)|^2\right\} \tag{2}$$

where w_p is the element used to minimize the difference of the direction p and N and M are the number of rows and columns of the image respectively. Therefore, the final equation of the Adaptive Local Binary Pattern (ALBP) is defined as it is shown in Eq. (3).

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - w_p \cdot g_c\right)2^p, \quad s(x) = \begin{cases} 1 & \text{if} \quad x \geq 0 \\ 0 & \text{if} \quad x < 0 \end{cases} \tag{3}$$

2.4 CLBP

The same research group that developed LBPV and ALBP presented another method called CLBP (Completed LBP), which tries to generalize and complete the information that the original method provides (Guo et al. 2010a, b, c). In this method, a local region of the image is represented by its central pixel and a Local Difference Sign-Magnitude Transformation (LDSMT). The LDSMT splits the local structure of the image into two complementary components: the sign difference that matches with the classic LBP, called CLBP_S and the magnitude difference CLBP_M, which is defined using Eq. (4).

$$\mathrm{CLBP\_M}_{P,R} = \sum_{p=0}^{P-1} t\left(g_p - g_c, c\right)2^p, \quad t(x,c) = \begin{cases} 1 & \text{si} \quad x \geq c \\ 0 & \text{si} \quad x < c \end{cases} \tag{4}$$

where c is a threshold defined adaptively. Usually, the average value of all the magnitude differences in the image is used.

2.5 LBPV

Guo and his colleagues proposed Local Binary Pattern Variance (LBPV) as a combination of LBP and a contrast distribution method (Guo et al. 2010a, b, c). LBPV uses the image variance as an adaptive weight to adjust the contribution of each value of the LBP in the histogram calculation. LBPV is calculated according to Eq. (5).

$$\mathrm{LBP}_{P,R} = \sum_{i=1}^{N}\sum_{j=1}^{M} w\left(\mathrm{LBP}_{P,R}(i,j), k\right), k \in [0, K], \tag{5}$$

where k represents the histogram values, K is the maximum value of the LBP and w is defined in Eq. (6).

$$w(\mathrm{LBP}_{P,R}(i,j),k) = \begin{cases} \mathrm{VAR}_{P,R}(i,j), & \mathrm{LBP}_{P,R}(i,j) = k \\ 0 & \text{in other case} \end{cases} \tag{6}$$

The neighborhood variance $VAR_{R,P}$ is defined in Eq. (7).

$$VAR_{P,R} = \frac{1}{P}\sum_{p=0}^{P-1}(g_p - \mu)^2, \quad (7)$$

where μ is the mean of the neighborhood.

2.6 LOSIB

The main goal of the Local Oriented Statistical Information Booster (LOSIB) proposed by García-Olalla et al. (2014), is to enhance the performance of texture descriptors. The main idea of LOSIB is to add local oriented statistical information computed along all pixels of the image.

This information is rarely taken into account when describing textures even though it provides very useful data about them. In this work, LOSIB is combined with other texture descriptors by concatenating it with the corresponding feature vectors.

The first step to obtain LOSIB is to extract the absolute differences d_p between the gray-level values g_c and g_p for all pixels c of the image, as shown in Eq. (8).

$$d_{p(x_c,y_c)} = |g_c - g_p| \quad (8)$$

Given a pixel c, the coordinates (x_p,y_p) of its neighbor p are extracted following Eq. (9).

$$\left(x_p, y_p\right) = \left(x_c + R\cos\left(\frac{2\pi p}{P}\right), \quad y_c - R\sin\left(\frac{2\pi p}{p}\right)\right) \quad (9)$$

The values of neighbors that are not in the grid center can be estimated by interpolating their connected pixels. Then, the mean of all differences along the same orientation is computed by means of Eq. (10), where N and M are the number of rows and columns of the image, respectively.

$$\mu_p = \frac{\sum_{x_c=1}^{M}\sum_{y_c=1}^{N} d_p(x_c, y_c)}{M \times N} \quad (10)$$

So in the end, LOSIB comprises as many features as neighbors in the neighborhood and gives information about the mean of the gray level difference for all the orientations along the image.

3 Experiments and Results

3.1 Outex

The Outex dataset has been used to evaluate the different description methods due to its high popularity in experiments involving texture description for the last years. Two different tests proposed by the Outex developers have been carried out: Outex_TC_00010 (TC10) and Outex_TC_00012 (TC12), both of them composed by 24 different textures. Each texture has been taken under three illumination conditions ("Horizon", "inca" and "tl84") and nine rotation angles (0°, 5°, 10°, 15°, 30°, 45°, 60°, 75° and 90°). Furthermore, 20 different patches without overlap of 128 × 128 pixels have been created for each texture, illumination and angle.

In this work, the same experimental setup used in the state of the art related to Outex has been chosen:

1. In the TC10 experiment, the classifier is trained with the illumination "inca" and an angle of 0° for each texture and the other eight angles in each texture for the same illumination are used for testing in the classification. Hence, the size of the training set is 480 (24 × 20) and the number of test set is 3480 images (24 × 8 × 20).
2. In the TC12 experiment, the classifier is training with the same training set of the first experiment composed by 480 images and the test set is composed of all the other two illumination images ("horizon" and "tl84"). In that case, the number of images in the test is 4320 (24 × 20 × 9) for each illumination.

In Fig. 3, a brief subset of the images is shown, which yield Outex and their different illumination conditions.

3.2 Results

The SVM (Support Vector Machine) was used as classifier, due to the high performance that it has achieved in this kind of experiments, for both tests: TC10 ("inca") and TC12 ("horizon" and "tl84"). Figure 4 depicts the achieved results. In contrast with what was expected, the tests carried out using only the LBP-based descriptors outperform in all the cases the corresponding descriptors concatenated with LOSIB. These results can be explained taken into account the high requirement of Outex against rotational invariance, which is not considered by LOSIB. In the work carried out by García-Olalla et al. (2014), the evaluated dataset (KTH TIPS2-a) was not focused in the rotation but in the illumination and scale, where LOSIB performance is higher.

Considering only the methods based in LBP, the best result was obtained using LBPV with 16 neighbors, which makes it a clear candidate to be used in the

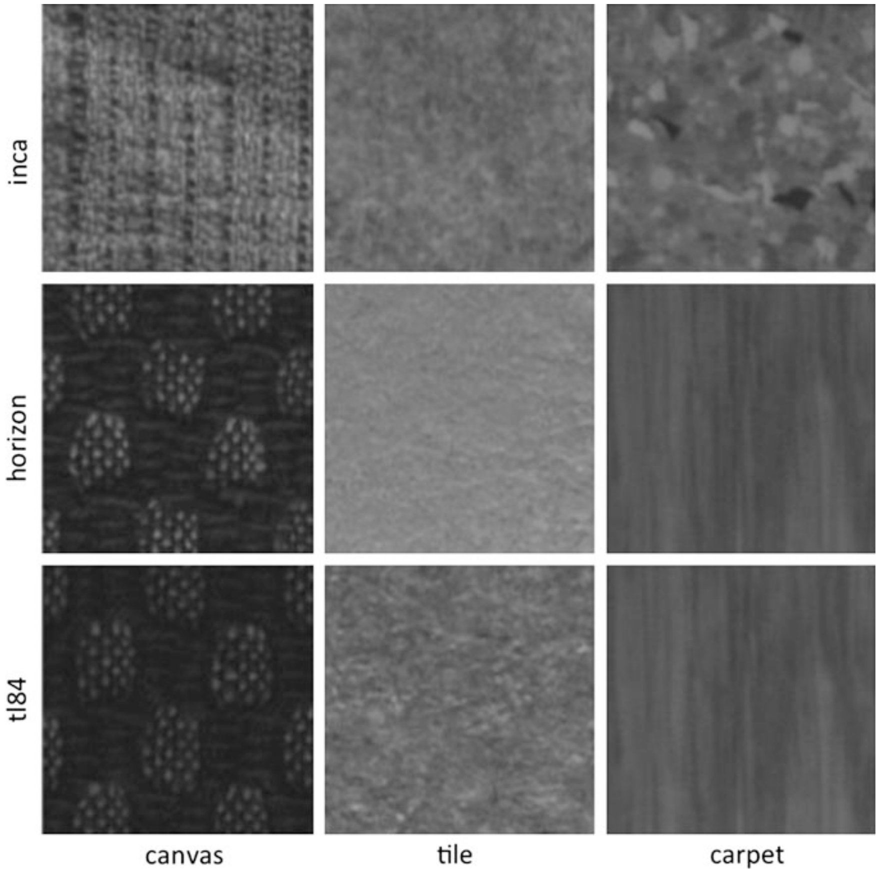

Fig. 3 Example of the Outex images. Each row corresponds to a different illumination type and each column to an example of the different textures

FRESVIDA project in order to detect the wear of inserts in milling processes. Regarding the results, it is remarkable the higher performance achieved by using a neighborhood of 16 instead of the smallest one of just 8.

In Table 1, the numeric results for each evaluated test using LBP variants are presented. The results of the LOSIB concatenations are not shown, due to the poor performance that they achieved (see Fig. 4).

The difference in the results for the three illuminations results is very significant: more than the 20% of hit rate in some cases. The LBPV has become the best descriptor for all the experiments, being the neighborhoods 8 and 16 the best solutions for TC10 and TC12 respectively.

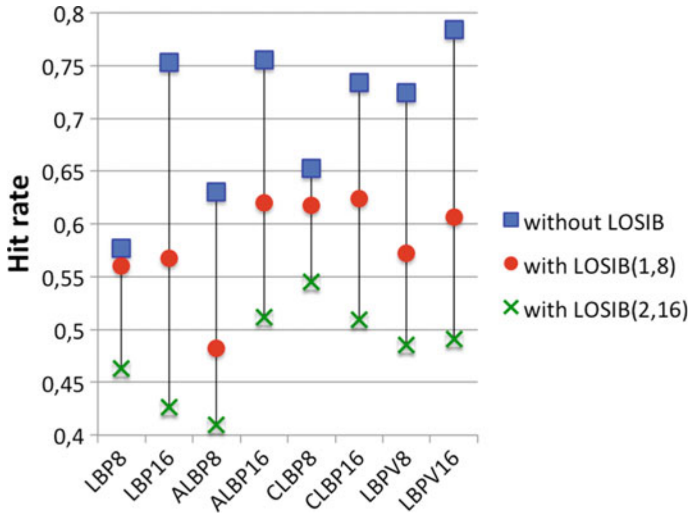

Fig. 4 Mean Hit rate for the three illuminations using LBP-based descriptors alone and also combined with LOSIB

Table 1 Hit rate for all the experiments evaluated using different methods based on LBP and the mean value of them

	TC10	TC12		Mean
	"inca"	"horizon"	"tl84"	
LBP8	0.6071	0.5590	0.5653	0.5771
LBP16	0.8313	0.6917	0.7366	0.7532
ALBP8	0.7518	0.5606	0.5780	0.6301
ALBP16	0.8247	0.7044	0.7377	0.7556
CLBP8	0.8115	0.5630	0.5843	0.6530
CLBP16	0.8440	0.6572	0.7013	0.7342
LBPV8	0.8607	0.6387	0.6727	0.7240
LBPV16	0.8495	0.7192	0.7833	**0.7840**

The best result is written in *bold*

4 Conclusions

In this paper an assessment is carried out, of different texture description techniques in a system for milling machines tool wear monitoring. Specifically, these methods are evaluated using the image dataset Outex—a state-of-the-art dataset in texture classification. The results of the experiments have shown that the methods based on Local Binary Patterns work quite well describing textures even if they have been rotated or subjected to changes in illumination. Classifications, carried out using SVM, indicate that the best method has been LBPV, which achieved a mean hit rate of 78.40% over the three experiments with different illuminations. It is remarkable that the best hit rate achieved using this descriptor was 86.07%, obtained with the “inca” illumination. Such results allow us to consider using this technique in an automatic tool wear monitoring system based on image processing, under the framework of the FRESVIDA project.

Another test carried out in this paper consisted in combining the aforementioned descriptors with LOSIB, a texture descriptor presented in 2014 that has proved to be very successful in combination with LBP. However, the results in this case have been much lower than the ones obtained using both methods separately, mainly because the Outex dataset was designed mainly to assess rotation invariant methods, as the images of each class are rotated.

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