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Tool wear classification using LBP-based descriptors combined with LOSIB-based enhancers

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Abstract

In this paper, an automatic process to determine tool wear in machining procedures has been developed using computer vision and texture recognition techniques. Two different methods based on Local Binary Pattern (LBP) were evaluated combined with the LOSIB texture booster (Local Oriented Statistical Information Booster). The dataset used is composed by 577 images representing different wear of inserts. Two classifications were carried out: (i) a binary classification with Low-High discrimination and (ii) a ternary classification with Low-Medium-High discrimination. The results show that when combining LBP with LOSIB, all the other methods are outperformed featuring an 80.58% of accuracy in the binary classification and a 67.76% in the ternary classification. These results are very interesting for industry due to the possible savings in terms of cost and time if it is applied in a tool condition monitoring system (TCMS).

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Keywords: texture description; tool wear; monitoring; LOSIB; LBP; TCM

1. Main text

Development of on-line measurement systems to detect the wear level of metal cutting inserts is an issue of utmost importance for the control of automated production systems. These tool condition monitoring systems (TCMS) help to reduce operation costs, since supervision of operator is no longer required. Moreover, decision

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making about the optimum time for insert replacement is done following objective criteria. Nowadays, this facet is becoming more and more important due to the high speed machining trend, which makes tool life decrease significantly.

Weckenmann et al. [1] reported that cost of cutting tools and their replacement account 3-12% of total production costs. For this reason, it is clear that a considerable amount of money can be saved if we increase the efficiency of tool wear monitoring |2]. Furthermore, on modern machines about 20% of the non-productive time is due to tool failure [3].

For these reasons, online monitoring of tool wear has becoming a very interesting research area, trying to avoid the subjective criteria of operators by using objective facts to predict the right moment for tool replacement. Lim [4] reported a saving up to 40% of costs by using wear sensors. Some other recent works referencing this feature are detailed in [5-7].

In this context the use of computer vision and texture analysis is of interest to develop accurate and efficient methods to predict tool wear level. Texture analysis is a challenging open problem in computer vision, which tries to describe spatial variations of grey levels through the pixels in an image. Nowadays, there are multiple fields that take advantage from automatic processes based on texture analysis. For example, in the biological field, Alegre et al. [8] proposed a texture and moment based classification of the boar sperm acrosome integrity obtaining very promising results. González-Castro et al. [9] proposed an adaptive method with no need of training for texture classification based on pattern spectrum description.

Wavelet transform information or local descriptors such as Local Binary Pattern (LBP) proposed by Ojala et al. [10] are very well known techniques with high performance in several fields. LBP has been taken into account for doing several variants due to its simplicity and high capabilities. García-Olalla et al. [11] proposed an adaptive LBP method based on statistical oriented information. Guo and his researching team have carried out several modifications to LBP such as LBPV [12], ALBP [13] or CLBP [14]. In quality control processes, a modified LBP variant was used by Tajeripour et al. [15] to detect defects in fabrics, obtaining results higher than 95% of hit rate.

The aim of this paper is to estimate the wear of cutting inserts using texture descriptors based on LBP [10] and LOSIB [16], applying both of them to the wear regions of the inserts. So that, decision making about the right time for tool replacement can be improved by means of objective reasons.

The rest of the paper is organized as follows. In section 2, the methodology of this work is described. The experiments and dataset information are shown in section 3. Finally, in section 4, conclusions are discussed.

2. Methodology

2.1. Local Binary Pattern variants

The main idea of LBP [10] is to describe the texture of grayscale images by extracting their local spatial structure. Firstly, for each pixel, a pattern code is calculated by comparing its value with all the values of the members of a previously defined neighborhood (Eq. 1):

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

where g_c is the value of the central pixel, g_p is the value of its neighbor p, P is the number of neighbors and R is the radius of the neighborhood. The neighbors are equally distributed along the circumference of radius R and centre g_c. Afterwards, the whole image is characterized by means of a histogram of its LBP pattern codes.

Despite LBP is grey scale invariant, rotating an image results in a different LBP pattern for each pixel. In order to solve this problem, Ojala et al. [17] achieved invariance to rotation by assigning a unique identifier to each rotated LBP. In their work, the following equation (Eq. 2) was defined:

$$LBP_{P,R}^{ri} = \min\left\{ROR\left(LBP_{P,R}, i\right) \middle| \; i = 0, 1, \ldots, P-1\right\} \tag{2}$$

where ROR(x,i) performs a circular bit-wise right shift i times on the P-bit number x. In this way, for example the patterns 11101101 and 10111101 will lead to the same output value.

As mentioned by Ojala et al. in the same work, some LBP, which contain very few spatial transition called "uniform", appear to be primal properties of local textures. Formally, the U(X) is a uniformity measure which is equal to the number of bitwise transitions in pattern X from 1 to 0 or from 0 to 1 taking into account that the transition is circular, so also the possible transition between the last and first bits of the pattern has to be considered. An LBP code X is defined as uniform if U(X) is less or equal than 2. Examples of uniform patterns are 11111111 (0 transitions), 00001000 (2 transitions), 10111111 (2 transitions) whereas 00010110 (4 transitions) or 00101010 (6 transitions) are examples of non-uniform patterns. The following operator, apart from being grey scale and rotation invariant, gather non-uniform patterns in the same group:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{P=0}^{P-1} s\left(g_p - g_c\right) \ if \ \ U\left(LBP_{P,R}\right) \le 2 \\ P+1 \ \ otherwise \end{cases} \tag{3}$$

where

$$U\left(LBP_{P,R}\right) = \left| s\left(g_{p-1} - g_c\right) - s\left(g_o - g_c\right) \right| + \sum_{p=1}^{P-1} \left| s\left(g_p - g_c\right) - s\left(g_{p-1} - g_c\right) \right| \tag{4}$$

There are only P+1 uniform patterns in a neighbor of P pixels. Each of these will have a label from 0 to P, according to the previous equation, which corresponds to the number of bits equal to 1 in the pattern. On the other hand, all non-uniform patterns will be labelled as P+1. Therefore, Eq. 3 produces P+2 output possible values. Finally, a histogram of P+2 bins is built in order to describe the whole image by computing Eq. 4 for each pixel of the image, yielding the feature vector of the image.

In this work, we have used Eq. 3. It will be called LBP henceforth for simplicity.

A Local Binary Pattern based method called CLBP (Complete Local Binary Pattern) [13] has been evaluated in order to compare the results with the original method. In their work, Guo et al. try to generalize and to complete the classical LBP. In this method, any local region is represented by its central pixel and a local difference sign-magnitude transform called LDSMT. LDSMT decomposes the image local structure into two complementary components: the difference signs and the difference magnitudes. In order to code both components, they proposed two operators, CLBP-Sign (CLBP_S) and CLBP-Magnitude (CLBP_M). Since all of them are in binary format, they can be combined to form the final CLBP histogram.

CLBP_S is equal to the classical LBP histogram and CLBP_M is defined as follows (Eq. 5):

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} t\left(m_p, c\, g_p\right) 2^p, \ t\left(x,c\right) = \begin{cases} 1 \ if \ \ x \ge c \\ 0 \ if \ \ x < c \end{cases} \tag{5}$$

where c is a threshold determined adaptively. In this case, c is assigned to the mean value of all the magnitude differences along the full image as Guo did in [13].

Finally, $\mathrm{CLBP}_{\mathrm{P,R}}^{\mathrm{riu2}}$ is obtained either concatenating or merging both operators.

2.2. Local Oriented Statistical Information Booster (LOSIB)

The main purpose of the Local Oriented Statistical Information Booster (LOSIB) proposed by García-Olalla et al. in [16] is to enhance the performance of a texture descriptor by adding local oriented statistical information computed along all pixels of the image.

This information is rarely taken into account when texture is described and it gives extremely useful information for texture discrimination. In this work, the combination of LOSIB with widely used texture descriptors was done by concatenating both vectors.

In order to obtain the LOSIB of an image, it is first necessary to extract the absolute differences d_p between the grey level values g_c and g_p, for all pixels c of the image using the Eq. 6:

$$d_{p(x_c, y_c) = |g_c - g_p|} \tag{6}$$

Given a pixel c, the coordinates (x_p, y_p) of its p-th neighbor are obtained by means of the following equation:

$$(x_p, y_p) = \left(x_c + R\cos\left(\frac{2\pi p}{P}\right), y_c - R\sin\left(\frac{2\pi p}{P}\right) \right) \tag{7}$$

The values of the neighbors that are not in the center of grids can be estimated by interpolation of their connected pixels. Then, the mean of all the differences along the same orientation is computed following Eq. 8:

$$\mu_p = \frac{\sum_{x_c=1}^{M} \sum_{y_c=1}^{N} d_p(x_c, y_c)}{M \times N} \tag{8}$$

where N and M are the number of rows and columns of the image, respectively.

Thereby, LOSIB will have as many features as neighbors are in the considered neighborhood and it represents the mean difference for all the orientations taken into account.

3. Experiments

3.1. Dataset

The original dataset was composed by 53 inserts. An example is shown in Fig. 1. The grey scale images of the inserts with masked background were subjected to a pre-processing step, which results in four images, one for each cutting edge. However, several regions with different level of wear could be determined in the same cutting edge image. In this paper, the goal was to use a dataset formed by images of the wear regions, avoiding the possibility of errors in the classification by the ambiguity of edge images containing different level of wear.

An example of extraction of wear is shown in Fig. 2. One can see that an image can contain regions with different levels of wear. This is one of the most important reasons why we create this dataset. Our cutting edge dataset was formed by 212 images. Extracting the wear regions of each image yield to a final dataset of 577 wear tool patches.

Some images of the new dataset are shown in Fig. 3. In the first row vertical regions are shown. The second and third rows contains horizontal regions.

We have evaluated our dataset using two different labelling carried out by an expert. This classification by the expert was qualitative without considering quantitative wear measurement, trying to reproduce the way of working in this type of industry. The first experiment consisted in distinguishing wear regions between Low (L) and High (H) wear. The second experiment was more challenging, trying to differentiate among three different grades of wear: Low (L), Medium (M) and High (H). It is important to notice that labelling and all evaluation carried out in this paper have been made just taking into account the texture information of the wear and not its shape.

3.2. Experimental Setup

A fast supervised classifier called Support Vector Machine was chosen in order to learn a model which can distinguish between two or three levels of wear. In both cases, a SVM with 'Least Squares' training algorithm and a linear kernel was used. We have tested several kernels but the linear one achieved the best results. A cross validation was also carried out using random samples of the dataset for training the classifier (70%) and the rest for testing (30%). This evaluation was run 10 times in order to avoid random results. We present on this paper the mean value of all the iterations.

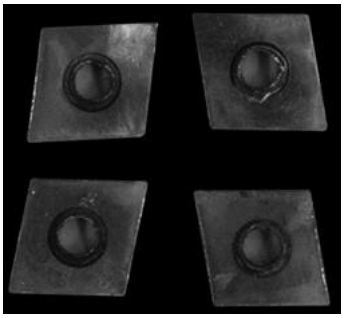

Fig. 1. First inserts dataset example.

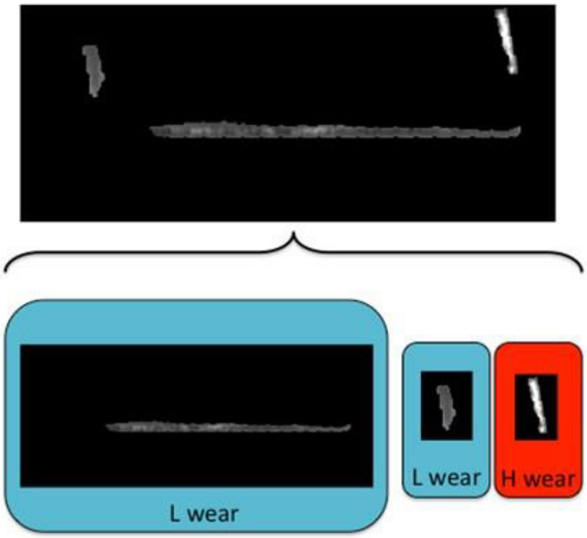

Fig. 2. Example of the cutting edge divided into regions.

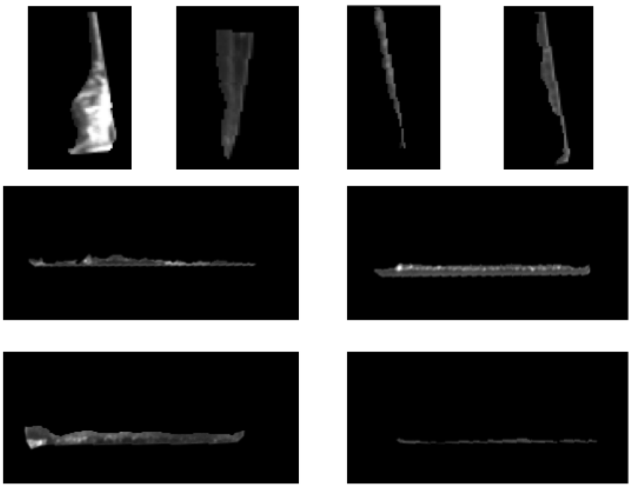

Fig. 3. Examples of the wear regions dataset.

4. Results

4.1. Results with LBP methods

The first experiment consisted of evaluating our dataset using just the classical texture descriptors based on LBP, explained in the previous section. Furthermore, LOSIB descriptor was used to describe by itself the images just to have a briefly idea of its own performance.

In Fig. 4, we can see a graphic with the results for the L-H classification. As it can be seen, all classical methods except the CLBP with 16 neighbors obtain better results than the LOSIB method by itself. In this dataset the use of a little neighborhood shows better results in the LBP descriptors due to the narrow shape of the region of interest. LBP with 8 neighbors and radius 1 achieved a 78.44% of hit rate against the LOSIB (2,16) that had a performance of 74.57%.

In Fig. 5, the results achieved by the three classes classification (L-M-H) are shown. It can be observed that the performance using this classification decreases due to complexity of discern among three classes instead of just two. In this experiment all the methods obtain better results using the small neighborhood in contrast with the binary classification, where LOSIB(2,16) achieved better results than LOSIB(1,8). The best result is again obtained when using LBP8, with a 67.30% of hit rate, while LOSIB(1,8) achieved just a poor 59.25%. However, LOSIB was developed not only for describing an image by itself but also for boosting the description of other methods. In the next section the results obtained when LBP methods are combined with LOSIB are shown.

4.2. Results with LBP+LOSIB methods

An experiment combining LOSIB with LBP based methods was carried out in order to determine the real performance of LOSIB as a booster. In Figure 6, a visual comparison is depicted to better understand the results in the binary classification. The horizontal lines show the four values obtained in the previous experiment, using just LBP and CLBP with 8 and 16 neighbors. The color of the bars is chosen to show the improvement of each fusion method with its base descriptors. It can be observed that in all cases the combination of LBP variant with LOSIB improves the performance of classification. In the case of CLBP16+LOSIB(1,8) the improvement is 32.92%, which is the highest difference obtained. The best result is achieved with LBP8+LOSIB(1,8) obtaining an 80.58% of hit rate, and an improvement of 2.73%.

In the ternary classification the results were similar (see Fig. 7). Also, the best result was achieved when using LBP8+LOSIB(1,8) with a 67.76% of hit rate. The highest improvement was obtained combining CLBP8 with LOSIB(1,8) obtaining a 67.36% of hit rate, better than the based CLBP8 method which achieves just 62.3% of hit rate. The results using three classes are worse than the results for two classes but they also give more information about the wear level of the inserts.

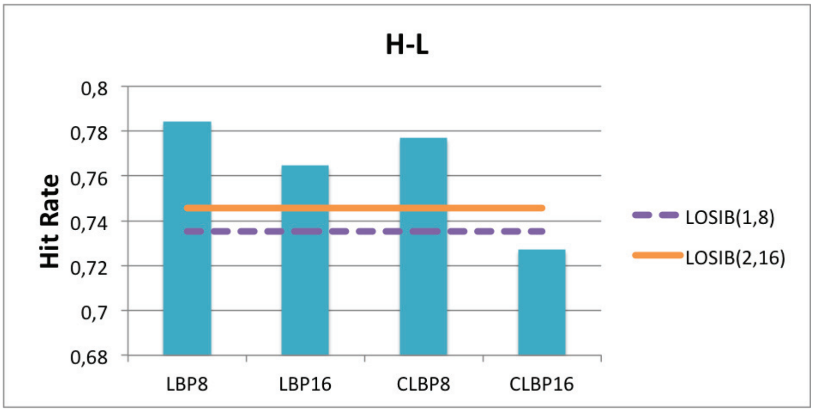

Fig. 4. Results using SVM and classical LBP and CLBP with different neighborhoods for the binary classification (H-L). In the horizontal lines results achieved by LOSIB.

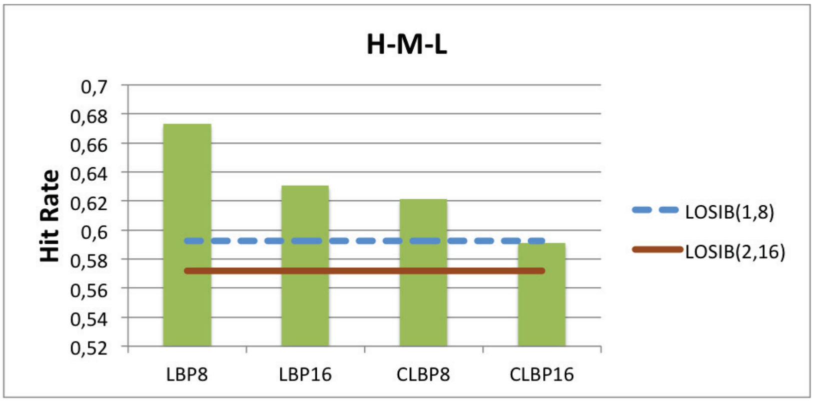

Fig. 5. Results using SVM and classical LBP and CLBP for the ternary (H-M-L) classification. In the horizontal lines results achieved by LOSIB.

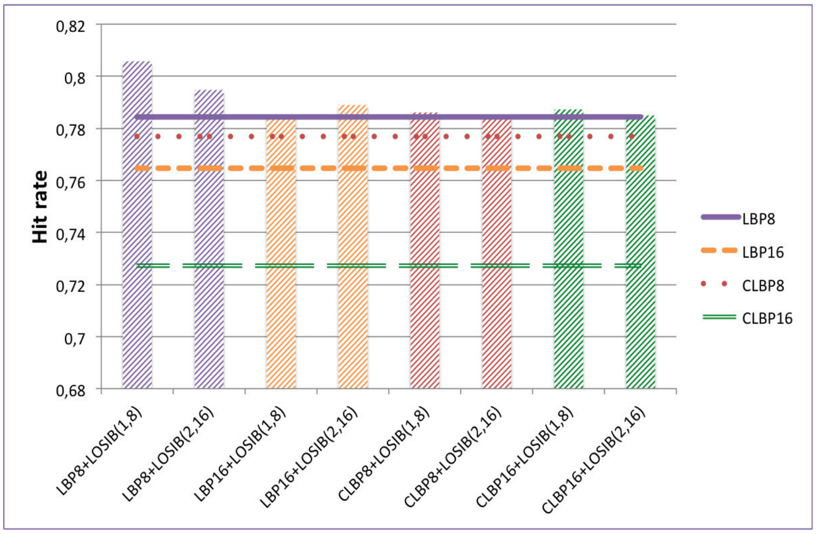

Fig. 6. Results using SVM and fusion of LBP and CLBP with LOSIB for the binary (H-L) classification.

5. Conclusions

In this work, an exhaustive evaluation and automatic classification of worn cutting inserts has been presented based on the wear level. For doing it, two local descriptors were tested: Local Binary Pattern (LBP) and one of its most used variants, Complete Local Binary Pattern (CLBP). Furthermore, the texture booster LOSIB (Local Oriented Statistical Information Booster) has been used to describe the wear and it has been combined with local techniques in order to improve the results. Two different classifications were carried out: a binary classification to discriminate between low and high wear and a ternary classification to discriminate among low, medium and high wear.

In the binary classification, the best results were achieved using LBP8 and LOSIB(1,8) with a 80.58% of hit rate, outperforming the based methods in more than a 2.7%. It is noticeable that in all the experiments the addition of LOSIB information improves the accuracy of the classification. When using CLBP, the highest increment was achieved combining LOSIB(1,8) with CLBP16, obtaining a 7.95% of improvement.

In the ternary classification, more challenging than binary classification, the best result was obtained also using LBP8 and LOSIB(1,8) with a 67.76% of hit rate, outperforming the LOSIB combination of all the based methods as in the binary one.

Both classification experiments are very interesting for manufacturing engineering in order to implement an automatic control process. Results are very promising due to the opportunity to determine the optimal time when an insert requires to be replaced. This can lead to significant savings in time with regard to traditional methods of manual checking or machined part/cutting time counting. Also, it can prevent from accidental tool breakage and part damage.

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