University of Groningen

Identification of milling inserts in situ based on a versatile machine vision system

Fernandez Robles, Laura; Azzopardi, George; Alegre, Enrique; Petkov, Nicolai; Castejón-Limasa, Manuel

Published in:
Journal of Manufacturing Systems

DOI:
[10.1016/j.jmsy.2017.08.002](https://doi.org/10.1016/j.jmsy.2017.08.002)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2017

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Fernandez Robles, L., Azzopardi, G., Alegre, E., Petkov, N., & Castejón-Limasa, M. (2017). Identification of milling inserts in situ based on a versatile machine vision system. *Journal of Manufacturing Systems*, 45, 48-57. <https://doi.org/10.1016/j.jmsy.2017.08.002>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Technical Paper

Identification of milling inserts *in situ* based on a versatile machine vision system

Laura Fernández-Robles^{a,b,*}, George Azzopardi^{b,c}, Enrique Alegre^a, Nicolai Petkov^b, Manuel Castejón-Limas^a

^a Industrial and Informatics Engineering School, University of León, Spain

^b Johann Bernoulli Institute for Mathematics and Computer Science, University of Groningen, The Netherlands

^c Intelligent Computer Systems, University of Malta, Malta

ARTICLE INFO

Article history:

Received 20 April 2017

Received in revised form 5 August 2017

Accepted 10 August 2017

Keywords:

Machine vision

Automatic inspection

Milling

Insert localization

ABSTRACT

This paper proposes a novel method for *in situ* localization of multiple inserts by means of machine vision techniques, a challenging issue in the field of tool wear monitoring. Most existing research works focus on evaluating the wear of isolated inserts after been manually extracted from the head tool. The method proposed solves this issue of paramount importance, as it frees the operator from continuously monitoring the machining process and allows the machine to continue operating without extracting the milling head for wear evaluation. We use trainable COSFIRE filters without requiring any manual intervention. This trainable approach is more versatile and generic than previous works on the topic, as it is not based on, and does not require, any domain knowledge. This allows an automatic application of the method to new machines without the need of specific knowledge on machine vision. We use an experimental dataset that we published to test the effectiveness of the method. We achieved very good performance with an F_1 score of 0.9674, in the identification of multiple milling head inserts. The proposed approach can be considered as a general framework for the localization and identification of machining pieces from images taken from mechanical monitoring systems.

© 2017 Published by Elsevier Ltd on behalf of The Society of Manufacturing Engineers.

1. Introduction

We have witnessed many works during the last decades on the implementation of tool wear monitoring (TWM) systems that aim at improving the quality, speed and manufacturing costs. This should not be a surprise considering that the impact of cutting tool failures due to wear and breakage on total production costs ranges from 3% to 12%. Along with this cost, 20% of non-productive time is due to tool failure and, moreover, tool wear is found to have a direct impact on the quality of surface finish and dimensional precision of the finished product [1].

Given these facts, the development of measurement systems to localize tool inserts and evaluate their wear level in milling processes is an issue of high importance.

* Corresponding author at: Industrial and Informatics Engineering School, University of León, 24071, Spain.

E-mail addresses: lfernandez@unileon.es

(L. Fernández-Robles), george.azzopardi@um.edu.mt

(G. Azzopardi), enrique.alegre@unileon.es (E. Alegre), n.petkov@rug.nl (N. Petkov),

manuel.castejon@unileon.es (M. Castejón-Limas).

In this paper we focus on the preliminary stage of tool wear monitoring by means of digital image processing techniques: the identification of multiple inserts in an image of the milling head. Fig. 1 shows the milling machine object of this study, Tecoi TRF cutting machine, and a close-up of the milling head tool. Most of the existing works relying on image processing techniques evaluate isolated inserts [2–4,1] rather than first localizing the inserts and their cutting edges on the milling head. Therefore requiring the extraction of the cutting head and the continuous presence of an operator during the machining process. On the contrary, this paper presents an automatic identification procedure that takes place *in situ* and does not interfere in the machining process: no human operator, no cutting head extraction, no stop during process. Other works evaluate tool condition in turning [5–7] or branching [8] rather than in milling and they do not need a precise localization of inserts.

To the best of our knowledge, two works deal with the localization of multiple inserts in milling heads with high number of inserts. In [9] we used a circular Hough transform to detect the screws that fasten the inserts. That method, however, suffered from insufficient ability to detect skewed screws which are typically found at the sides of the images. That approach is highly specific to solve

Fig. 1. (a) Milling machine. The green ellipses mark the two milling head tools of Tecoi TRF cutting machine. (b) Milling head tool. Inserts are fastened with circular screws. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

this particular problem since it is only valid for inserts fastened by circular screws. And more importantly, it required a lot of domain knowledge to set up the parameters of the system and could not be directly reproducible on another machine. As an improvement to the shortcomings of that previous work, the present paper proposes a more versatile and generic method that can be automatically tuned to localize multiple inserts in a milling machine. In another study [10] the authors used a basic template matching approach and obtained a low F_1 score (harmonic mean of precision and recall) of 86%.

After localizing the inserts, methods to determine which inserts are broken (if any) or wear level of the inserts should follow. In [11], we presented an efficient machine-vision-based method that detects broken inserts in milling heads. In [11] the localization of inserts was done using the domain knowledge-based method introduced in [9].

The approach that we propose in this paper makes use of a set of trainable COSFIRE (Combination Of Shifted Filter REsponses) filters [12] that are selective for inserts in different poses. Their capability to localize patterns similar to a prototype based on the arrangement of edges makes this approach very appealing for this application. COSFIRE filters enable us to have a generic approach, where no domain knowledge is required, since they can be automatically configured to be selective for any shape. The proposed approach can, therefore, be useful for other applications. In this paper, we present a method to efficiently use the baseline COSFIRE filters for the identification of inserts in machining processes.

COSFIRE filters have proved to be very effective in other fields for the detection of patterns based on the geometrical arrangement of lines and edges: vessel delineation [13], vascular bifurcations [14], handwritten digits recognition [15], detection and recognition of traffic signs in complex scenes [12] and object recognition [16,17]. This is the first time that an approach based on COSFIRE filters is used in the mechanical field.

2. Milling head images

To the best of our knowledge, there was no public repository that contains images of cutting heads from milling machines. Therefore, we created a collection comprising 144 of these images, which was originally published in [9]. Interested researchers have free access to this dataset.¹

Six milling heads, whose diameter is 14.5 cm and height 55 cm, each containing 30 cutting inserts screwed on 6 flutes along the tool perimeter, were captured. These inserts are rhombus-shaped with four 90° indexable cutting edges of 1 cm in length. The flutes overlap

Fig. 2. Schema of the capturing system.

vertically so that the last and first inserts of consecutive flutes are aligned. For this configuration, the camera and the milling head must be aligned on just 24 equally spaced positions. The number of inserts per image varies from 8 to 10.

We took the images with a monochrome camera, model Genie M1280 1/3", with an active resolution of 1280 × 960 pixels. A fixed lens (AZURE-2514MM) with focal length of 25 mm and 2 mega pixel resolution was used. In order to enhance [18] the grayscale images capturing capability, we used two compact bar shape structures with high intensity LED arrays (BDBL-R(IR)82/16H). Fig. 2 illustrates the schema of the capturing system.

Along with the dataset, we provide ground truth information. It comprehends a list of coordinates localizing the center of the screws fastening the inserts and a black background mask with 40-pixel radii white circles centered around the concerned positions.² For the definition of the ground truth, we have discarded partly visible inserts on each image. Fig. 3 illustrates some milling head images and their corresponding ground truth masks.

3. Method

3.1. Overview

We first apply the contrast-limited adaptive histogram equalization (CLAHE) method [19] to improve the contrast of the images and facilitate the detection of edges.

In order to detect a particular object in an image, COSFIRE filters are first configured by using some training patterns, also referred to as prototypes. We obtain a prototype pattern by extracting a delimited area – region of interest (ROI) – containing one of the inserts in a representative image, Fig. 4. The ROIs are only needed in the training phase and they are used to configure COSFIRE filters. The center points of these ROIs are given in the ground truth, while their heights and widths are defined as fixed pre-calibrated values,

¹ The dataset can be downloaded from <http://www.computervisiononline.com/dataset/edge-milling-heads>.

² An insert is considered correctly detected if it is localized within the given bounds of its screw in the ground truth.

Fig. 3. Images from the dataset (a–c) and their corresponding ground truth masks (d–f).

Fig. 4. Selection of the region of interest: (a) Input image (of size 1280 × 960 pixels). (b) Prototypical insert (image of size 210 × 210 pixels, cutting edges are 1 cm length). (c) Selection of the ROI. (d) Mask that mark out the area of the ROI.

in this case we set the size of the ROIs to 210 × 210 pixels. At testing phase, the COSFIRE filters are then able to localize the inserts without information about the ROIs.

COSFIRE filters [12] combine the responses of 2D Gabor filters at specific locations around a given point. Gabor filters [20] are selected by establishing their characteristic directions and the locations at which their responses are taken. Consequently, the resulting COSFIRE filter only responds to inserts similar in local spatial arrangement to that of the prototype. In this case, the most dominant edges are found on the sides of the insert, around the screw and on the top right crack, Fig. 4.

3.2. Gabor filters

We denote by $h_{\lambda,\theta}(x,y)$ a Gabor function with a given wavelength λ and orientation θ :

$$h_{\lambda,\theta}(x,y) = e^{-(u^2 + \gamma^2 v^2 / 2\sigma^2)} \cos\left(2\pi \frac{u}{\lambda} + \zeta\right) \quad (1)$$

$$u = x \cos(\theta) + y \sin(\theta) \quad (2)$$

$$v = -x \sin(\theta) + y \cos(\theta) \quad (3)$$

where $\gamma = 0.5$ is the aspect ratio that specifies the ellipticity of the support of the Gabor function; σ determines the size of the support,

and $\zeta = \pi/2$ is the phase offset that determines the shape of the Gabor function.³

We denote by $g_{\lambda,\theta}(x,y)$ the response of a Gabor filter to a grayscale input image I :

$$g_{\lambda,\theta}(x,y) = I * h_{\lambda,\theta}(x,y) \quad (4)$$

Gabor functions are normalized in such a way so all positive values sum up to 1 whereas all negative values sum up to -1 . In this way, the response to a local pattern of constant intensity is 0 even for symmetrical filters ($\zeta \in \{0, \pi\}$) and the largest response to a line of width w is achieved using a symmetrical filter with $\lambda = 2w$. We threshold the responses of Gabor filters at a fraction $t_1 = 0.1$ of the maximum response of $g_{\lambda,\theta}(x,y)$. In this way, we eliminate negative and small positive responses that are produced due to noise.

3.3. Configuration of COSFIRE filters

A COSFIRE filter is configured by determining the geometrical properties of the lines and edges in the neighbourhood of a specified point of interest, which in this case is the centre of a screw. The neighbourhood is defined by a set of concentric circles of given radii. We first superimpose the responses of a bank of Gabor filters

³ For more details about Gabor filters and the use of their parameters such as the aspect ratio or the standard deviation of the Gaussian envelope, we refer the reader to [21–26].

Table 1

Set of tuples that describe three contour parts of the prototype shown in Fig. 4 for a circle with radius $\rho = 107$ pixels.

i	λ_i	θ_i	ρ_i	ϕ_i
1	6	$15\pi/8$	107	0.7
2	6	$5\pi/8$	107	1.22
3	6	π	107	4.08

with one scale ($\lambda = 6$) and 16 orientations ($\theta = \{0, \pi/8, \dots\}$). For each local maximum Gabor filter response along these circles we consider the Gabor filters that give a response greater than a fraction $t_2 = 0.75$ of the maximum Gabor filter response at that position. We then create a 4-tuple $(\lambda, \theta, \rho, \phi)$ for every Gabor filter that satisfies the mentioned criterion: the wavelength λ and orientation θ of the Gabor filter define the characteristics of the concerned Gabor filter, while the distance ρ and polar angle ϕ define the position with respect to the center.

We denote by S_f a COSFIRE filter with a set of 4-tuples $(\lambda_i, \theta_i, \rho_i, \phi_i)$ that characterize the properties of the involved contour parts:

$$S_f = \{(\lambda_i, \theta_i, \rho_i, \phi_i) | i = 1, \dots, n_f\} \quad (5)$$

The subscript f stands for the pattern of interest (in this case an insert) around the screw and n_f stands for the number of involved contour parts.

For the ROI shown in Fig. 4, taking 25 concentric circles with equally spaced radii from 0 to 150 (the maximum radius of 150 pixels is half the diameter of the prototype insert), this method results in a COSFIRE filter with 127 tuples. Fig. 5(a) and (b) illustrates the consideration of Gabor filter responses along the circle with radius $\rho = 107$. The white cross in Fig. 5a indicates the point of interest and the white circle represents the locations of the Gabor filter responses considered around the point of interest for a given radius $\rho = 107$. The gray-level of a pixel represents the maximum value superposition of the responses of the bank of antisymmetric Gabor filters at that position. For that circle the automatic configuration determines 3 tuples; one for each point marked with labels a , b and c with parameter values specified in the set shown in Table 1. The three local maxima in the plot of Fig. 5b are respectively labelled and marked with pink dots in Fig. 5a. The third tuple $(\lambda_3 = 6, \theta_3 = \pi, \rho_3 = 107, \phi_3 = 4.08)$ describes a contour part with a wavelength of ($\lambda_3 = 6$) and an orientation of $\theta_3 = \pi$. These properties indicate that the concerned contour part is vertical and that it can be detected by a Gabor filter with preferred wavelength $\lambda_3 = 6$ and orientation $\theta_3 = \pi$, at a position of $\rho_3 = 107$ pixels to the bottom-left ($\phi_3 = 1.29\pi$) from the support center of the filter. This location is marked by the label c in Fig. 5a. In Fig. 5c we illustrate the structure of the resulting COSFIRE filter with 127 tuples. Each of the ellipses represents a tuple of the set of contour parts. Their size and orientation represent the scale and orientation parameters of the Gabor filters. The green enumerated ellipses represent the three contour parts along the circle with radius $\rho = 107$: ellipse 1 corresponds to the local maximum a , ellipse 2 to b and ellipse 3 to c . The bright blobs are intensity maps of the Gaussian functions that are used in the application step for blurring the responses of the Gabor filters.

3.4. Application of COSFIRE filters to milling head images

We apply a COSFIRE filter to an input image by first computing the responses of Gabor filters defined in the set of tuples. Then, for each position in an image, we combine the Gabor filter responses whose locations are specified by the polar coordinates in the set of tuples, and combine them with a multivariate output function.

3.4.1. Blurring and shifting

Before computing the output function of a COSFIRE filter, we first blur the Gabor filter responses in order to allow for some spatial tolerance of the involved contour parts. The Gabor filter responses are blurred by centering a Gaussian function map with standard deviation σ around every pixel and taking the weighted maximum. The standard deviation is a linear function of the distance ρ from the centre of the COSFIRE filter [12]:

$$\sigma_i = \sigma_0 + \alpha \rho_i \quad (6)$$

We use the default parameter values $\sigma_0 = 0.67$ and $\alpha = 0.1$ as suggested in [12]. The blurred response for the tuple $(\lambda_i, \theta_i, \rho_i, \phi_i)$ is defined as:

$$b_{\lambda_i, \theta_i, \rho_i}(x, y) \stackrel{\text{def}}{=} \max_{x', y'} \{g_{\lambda_i, \theta_i}(x - x', y - y') \times G_{\sigma_i}(x', y')\} \quad (7)$$

where $-3\sigma \leq x', y' \leq 3\sigma$.

Instead of retrieving the Gabor filter responses using the polar coordinates specified in tuples of the filter with respect to each pixel in the image, we shift the blurred responses of each Gabor filter by a distance of ρ_i in the opposite direction to ϕ_i . In polar coordinates, we can express this shift as $(\rho_i, \phi_i + \pi)$, whereas in Cartesian coordinates it is described as an increment $(\Delta x_i, \Delta y_i)$ where $\Delta x_i = -\rho_i \cos \phi_i$ and $\Delta y_i = -\rho_i \sin \phi_i$. We denote by $s_{\lambda_i, \theta_i, \rho_i, \phi_i}(x, y)$ the blurred and shifted response of the Gabor filter specified by the tuple $(\lambda_i, \theta_i, \rho_i, \phi_i)$ in the set S_f :

$$s_{\lambda_i, \theta_i, \rho_i, \phi_i}(x, y) = b_{\lambda_i, \theta_i, \rho_i}(x - \Delta x_i, y - \Delta y_i) \quad (8)$$

3.4.2. Response of a COSFIRE filter

In the work published in [12] the response of a COSFIRE filter is defined as the geometric mean of all blurred and shifted responses of the involved Gabor filters as defined in Eq. (9). This is a hard AND-type function as the absence of only one of the preferred contour parts suppresses completely the response of the COSFIRE filter, onwards named Hard Geometric Mean (HGM). Here, we experiment with two other softer output functions, namely arithmetic mean (AM) and soft geometric mean (SGM), defined in Eqs. (10) and (11), respectively.

$$r_{S_f}(x, y) \stackrel{\text{def}}{=} \left| \left(\prod_{i=1}^{|S_f|} (s_{\lambda_i, \theta_i, \rho_i, \phi_i}(x, y)) \right)^{1/|S_f|} \right|_{t_3} \quad (9)$$

$$r_{S_f}(x, y) \stackrel{\text{def}}{=} \left| \frac{1}{|S_f|} \left(\sum_{i=1}^{|S_f|} (s_{\lambda_i, \theta_i, \rho_i, \phi_i}(x, y)) \right) \right|_{t_3} \quad (10)$$

$$r_{S_f}(x, y) \stackrel{\text{def}}{=} \left| \left(\prod_{i=1}^{|S_f|} (s_{\lambda_i, \theta_i, \rho_i, \phi_i}(x, y) + \epsilon) \right)^{1/|S_f|} \right|_{t_3} \quad (11)$$

where $|\cdot|_{t_3}$ means that the response is thresholded at a fraction t_3 of the maximum across all coordinates (x, y) . The parameter ϵ in Eq. (11) is a very small value in order to avoid complete suppression by omitted contour parts. In this work, we set $\epsilon = 10^{-6}$. In this way a COSFIRE filter that uses a SGM output function always gives a response greater than zero. As for the AM function, the omission of a contour part has a lower effect in the response of a COSFIRE filter than SGM or HGM.

From the COSFIRE response map $r_{S_f}(x, y)$, we first choose the local maxima. Then, if two local maxima are within a Euclidean distance of 130 pixels, we only keep the point with the strongest response. Due to the shape of the milling cutting head and the conditions of the image capture, inserts are always separated by at least 130 pixels. We call these points, positive responses.

Fig. 5. Configuration of a COSFIRE filter: (a) Superposition of the response maps of a bank of Gabor filters. (b) The maximum Gabor filter responses along the depicted circle in (a). (c) Structure of the COSFIRE filter.

Fig. 6. (a) Input image. The framed area shows (top) the pattern of interest selected for the configuration and (bottom) the structure of the COSFIRE filter that is configured with this pattern. (b) Responses of the Gabor filters that define the contour parts found along the circle with radius $\rho = 107$. (c) Blurred and shifted Gabor responses. (d) Binary output of the COSFIRE filter computed with SGM and $t_3 = 0.15$.

Fig. 6 shows a demonstration example of the application of a COSFIRE filter to detect inserts. In this example, the COSFIRE filter is applied with the SGM function and has 127 tuples. The blurred and shifted response maps correspond to the tuples in the configured set. The filter responds in locations where there is an identical pattern or a pattern similar to the prototypical insert. In this example, the maximum response – marked with a red 'x' – is reached in the center of the prototype insert that was used to configure this COSFIRE filter and the other four local maxima correspond to similar inserts.

Although COSFIRE filters can achieve tolerance to rotation, scale and reflection [12], in this application it was not necessary to apply any invariances to such geometrical transformations.

4. Experiments

The dataset is split in two subsets, training and test. The training set is formed by the images of the dataset separated by 13 snapshots with numbers 0001, 0014, 0028, 0042, 0056, 0070, 0084, 0098, 0112 and 0126. The other 134 images form the test set. The flowcharts of the training and test experimental setups are shown in Fig. 7.

We configure filters in an iterative process by using inserts from the training images. We start by choosing a random insert from the training images to be the first prototype f_1 and use it to configure a COSFIRE filter S_{f_1} . Then, we apply this filter to all the images in the training set. We set the value of the parameter t_3 in such a way to produce the highest number of correctly detected inserts and no false positives, therefore achieving 100% precision. Fig. 8 shows the detected inserts with functions AM, HGM and SGM using the filter

Fig. 7. (a) Pipeline of the procedures applied to the training set for automatic training. (b) Pipeline of the procedures applied to the test set for method evaluation.

S_{f_1} for the prototype insert shown in Fig. 4b. We automatically set the threshold t_3 to 0.0776, 0.0135 and 0.0137 for the AM, HGM and SGM output functions, which results in 48, 22 and 56 correct detections, respectively. In total, there are 86 inserts in the 10 training images. Thus, this COSFIRE filter detects 65.12% of the inserts using SGM, and no false positives.

In the second iteration, we randomly choose one of the inserts that was not detected by the first filter S_{f_1} and we call it prototype f_2 . We use this prototype to configure a second COSFIRE filter S_{f_2} . Then, we apply this filter to the 10 images of the training set and determine the t_3 parameter values that yield to 100% precision. Filter S_{f_2} detects a number of inserts, some already detected by filter S_{f_1} and some new detections. For example, S_{f_2} with SGM correctly detects 52 inserts, of which 34 coincide with the inserts detected by S_{f_1} and 18 are newly detected ones. At this point, we have detected a total of 74 inserts out of 86.

The process successively continues until all the 86 inserts in the training set are detected. The number of filters needed for each output function in each experiment are reported in Table 2. Fig. 9 shows the set of inserts that was configured in the first experiment for each output function.

We apply the set of configured COSFIRE filters to the test set and compute the results in terms of precision, recall and their harmonic mean, also known as F_1 score:

$$F_1 = 2 \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

Recall is the percentage of true inserts that are successfully detected, $\text{Recall} = TP/(TP + FN)$. Precision is the percentage of correctly detected inserts from all positive response points, $\text{Precision} = TP/(TP + FP)$. TP , FP and FN stand for true positives, false positives and false negatives, respectively.

Table 2

Results of five experiments for the different output functions: arithmetic mean (AM), hard geometric mean (HGM), soft geometric mean (SGM). The sixth and seventh rows of each method show the means and standard deviations (SDs) of the corresponding columns, respectively. The heading #F stands for the number of filters, #T stands for the total number of tuples configured in all filters in the corresponding experiments, while F_1 is the harmonic mean of precision and recall. TM stands for template matching. Average results over 5 experiments are highlighted in bold.

	Exp #	#F	#T	Precision	Recall	F_1
AM	1	13	2026	95.34	93.58	94.45
	2	11	1639	95.99	92.61	94.27
	3	14	2127	94.88	94.81	95.02
	4	13	2009	95.23	96.31	94.16
	5	12	1830	94.26	95.25	94.75
	Mean	12.6	1926.2	95.14	94.15	94.64
	SD	1.14	192.92	0.006	0.010	0.003
HGM	1	9	1378	98.98	94.63	96.76
	2	11	1721	98.45	94.99	96.81
	3	9	1377	98.90	94.82	96.81
	4	10	1539	98.73	95.69	97.19
	5	10	1497	98.17	94.37	96.23
	Mean	9.8	1502.4	98.65	94.90	96.74
	SD	0.84	141.73	0.003	0.005	0.003
SGM	1	7	1052	97.16	96.130	96.64
	2	7	1089	96.42	96.92	79.67
	3	7	1118	95.52	97.54	96.52
	4	8	1188	97.50	95.87	96.68
	5	7	1097	97.15	95.87	96.51
	Mean	7.2	1108.8	96.75	96.47	96.60
	SD	0.447	50.29	0.008	0.007	0.001
TM [10]	1	–	–	82	89	86
Hough [9]	1	–	–	100	67.03	80.26

Fig. 8. Detection results on the entire training set with the COSFIRE filter that is configured with the prototype insert shown in Fig. 4b. Above each rectangle, a colored square indicates by which output function the insert is detected; red denotes SGM, yellow HGM and green AM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

We execute five experiments for each kind of output function in order to compensate for the random selection of prototypes and we compute average results.

5. Results

We evaluated the performance of the detection of inserts by a set of COSFIRE filters and we compared results using different output functions. Results are shown in Table 2. With AM, we configured

an average of 12.6 COSFIRE filters that we applied to the test set yielding an average F_1 score of 94.64%. We configured a set of 9.8 filters for HGM reaching an F_1 score of 96.74%. SGM required only an average of 7.2 filters and it achieved 96.60% F_1 score. We can conclude that the output functions based on geometric mean are more appropriate than the arithmetic mean for detecting inserts. The difference between HGM and SGM lies in precision and recall results and the number of filters used. SGM requires less computational resources since it needs less filters to reach a similar F_1 score. SGM

Fig. 9. Set of prototypical inserts that was needed to detect all inserts of the training set with 100% precision and 100% recall with AM (first two rows), HGM (third row) and SGM (forth row) output function in the first experiment.

is more appropriate when a high recall is needed. On the contrary, HGM is more convenient when a high precision is craved.

We changed the values of the parameter t_3 in order to investigate its effect. For each COSFIRE filter, we added to (or subtracted from) the corresponding learned threshold value t_3 an offset value in steps of 0.01. Precision increases and recall decreases with an increasing offset value (Fig. 10). For all the studied function outputs, the maximum F_1 score was reached at values of the threshold parameter t_3 with 0 offset. This demonstrates the generalization ability of our training procedure.

In Fig. 11, we show examples of the yielded results. Particularly, we show some inserts that have not been detected (false negatives) and some localized inserts that do not actually correspond to any insert (false positives). All inserts that were not detected are localized on the sides of the images irrespective of the output function evaluated. False positives are due to the similarity of the shape of same parts of the background of the milling head in relation to the shape of an insert.

6. Discussion

The proposed computer-vision-based system is designed to take the images while the machine is in its resting position, without interfering normal operation. The machining process studied in this research is performed in a single pass across very thick and long plates (up to 12 cm and 42 m, respectively) and then the head tool rests for periods ranging from 5 to 30 min while a new plate is prepared to be machined. Regular times for localizing the inserts using Matlab on a personal computer with a 2 GHz processor and 8 GB RAM are inferior to a minute in all cases. The time required for a later evaluation of tool wear is below 3 min [11]. Thus, the method proposed effectively uses the resting period to perform all the calculations. The training phase takes around 10 min and is done just the first time that the system is introduced to a new machine. There is no need of training after the replacement of inserts. The setting-up of the system is an automatic process that does not need specific knowledge of computer vision, in contrast to previous works [9].

Fig. 10. Precision-recall curves of the results obtained for each of the COSFIRE output functions: arithmetic mean (AM), hard geometric mean (HGM) and soft geometric mean (SGM) by varying the threshold t_3 .

In a previous work [10] we applied template matching to this problem and obtained lower performance (F_1 score 86%, precision 82% and recall 89% on the same dataset, Table 2) than those obtained with the approach reported in this paper. In that work, first the authors preprocessed the images by applying Canny's algorithm to the input image followed by a dilation of the edge map with a flat diamond-shaped structuring element of size 1 pixel. Then they performed a normalized cross-correlation to measure the correspondence between each template and the considered window in the input image. The response of the template matching was considered as the two best correspondences per input image and template. The same test and training sets as in this work were used for obtaining the experimental results.

We also used the circular Hough transform to localize the screws that fasten the inserts in [9]. In that case we used the knowledge that an insert is characterized by a screw in the middle and used circular Hough transform to detect such screws.

The approach that we propose is far more versatile as it can also be applied to identify any tool or part without using domain knowledge. This is particularly important in other machine vision applications with objects of interest that might be very different than the inserts in the concerned application.

Fig. 11. Examples of false positives (a–c) and false negatives (d–f). True positives are marked with white crosses, false positives with red crosses and false negatives with red rectangles.

The presented approach achieved better results than those achieved in [10,9] as shown in Table 2. In particular, it showed better precision, which is of outstanding importance for this case study. The precision obtained with template matching [10] was 82% and with Hough transform [9] was 67.07% while in this paper we achieved 98.65%.

Given the characteristics of the dataset, the same insert appears in 7–10 images in different positions and poses due to the rotation of 15° of the head tool from one snapshot to the following one. Notable is the fact that all unique inserts have been correctly localized at least once with all output functions.

7. Conclusions

In this paper we presented a versatile method for the localization of inserts in a milling head tool that contains a high number of inserts. This method relies on machine vision techniques, in particular, trainable COSFIRE filters. We automatically configured a set of COSFIRE filters with a small training set of only 10 images. We computed and compared results with three different output functions, hard geometric mean, soft geometric mean and arithmetic mean.

The proposed approach achieved very good performance in the identification of multiple milling head inserts with an F_1 score of 96.74% using hard geometric mean output function. That performance could not be achieved with alternative methods based on template matching or circular Hough transform. The approach proposed is more versatile and generic as it does not use domain knowledge, but rather it determines the geometrical features of a prototype pattern of interest in an automatic configuration procedure. The trainable character of the proposed approach makes it suitable to other visual quality inspection applications.

Acknowledgments

This work has been supported by DPI2012-36166 grant from the Spanish Government. We thank the company TECOI for providing us an edge profile milling head tool and the inserts to create our dataset and evaluate the proposed system.

References

- [1] Zhang C, Zhang J. On-line tool wear measurement for ball-end milling cutter based on machine vision. *Comput Ind* 2013;64(6):708–19, <http://dx.doi.org/10.1016/j.compind.2013.03.010>.
- [2] Lim T, Ratnam M. Edge detection and measurement of nose radii of cutting tool inserts from scanned 2-d images. *Opt Lasers Eng* 2012;50(11):1628–42, <http://dx.doi.org/10.1016/j.optlaseng.2012.05.007>.
- [3] Szydłowski M, Powalka B, Matuszak M, Kochmanski P. Machine vision micro-milling tool wear inspection by image reconstruction and light reflectance. *Precis Eng* 2016;44:236–44, <http://dx.doi.org/10.1016/j.precisioneng.2016.01.003>.
- [4] Xiong G, Liu J, Avila A. Cutting tool wear measurement by using active contour model based image processing. In: *International Conference on Mechatronics and Automation (ICMA)*; 2011. p. 670–5, <http://dx.doi.org/10.1109/ICMA.2011.5985741>.
- [5] Bhat NN, Dutta S, Vashisth T, Pal S, Pal SK, Sen R. Tool condition monitoring by SVM classification of machined surface images in turning. *Int J Adv Manuf Technol* 2016;83(9):1487–502, <http://dx.doi.org/10.1007/s00170-015-7441-3>.
- [6] Dutta S, Pal S, Sen R. Tool condition monitoring in turning by applying machine vision. *ASME J Manuf Sci Eng* 2016;138(5):051008, <http://dx.doi.org/10.1115/1.4031770>.
- [7] Dutta S, Pal SK, Sen R. On-machine tool prediction of flank wear from machined surface images using texture analyses and support vector regression. *Precis Eng* 2016;43:34–42, <http://dx.doi.org/10.1016/j.precisioneng.2015.06.007>.
- [8] Loizou J, Tian W, Robertson J, Camelio J. Automated wear characterization for broaching tools based on machine vision systems. *J Manuf Syst* 2015;37(2):558–63, <http://dx.doi.org/10.1016/j.jmsy.2015.04.005>.
- [9] Fernández-Robles L, Azzopardi G, Alegre E, Petkov N. Cutting edge localisation in an edge profile milling head. In: *Computer Analysis of Images and Patterns*, vol. 9257 of *Lecture Notes in Computer Science*. Springer International Publishing; 2015. p. 336–47.
- [10] Aller-Ídrc:A:rtddclvarez N, FernÍdrc:A:rtddclvarez L, GonzÍdrc:A:rtddclvarez V, Alegre E. Detection of inserts in head milling

- tools using template matching. In: *Actas de las XXXVI Jornadas de Automática: rtdctica. Comitad: e: rtdc Espa Ltd: n: rtdcol de Automática: a: rtdctica de la IFAC (CEA-IFAC)*; 2015. p. 80–4 [in Spanish].
- [11] Fernández-Robles L, Azzopardi G, Alegre E, Petkov N. Machine-vision-based identification of broken inserts in edge profile milling heads. *Robot Comput Integr Manuf* 2017;44:276–83, <http://dx.doi.org/10.1016/j.rcim.2016.10.004>.
 - [12] Azzopardi G, Petkov N. Trainable Ldc: COSFIRE: rtdc filters for keypoint detection and pattern recognition. *IEEE Trans Pattern Anal Mach Intell* 2013;35(2):490–503, <http://dx.doi.org/10.1109/TPAMI.2012.106>.
 - [13] Azzopardi G, Strisciuglio N, Vento M, Petkov N. Trainable COSFIRE filters for vessel delineation with application to retinal images. *Med Image Anal* 2015;19(1):46–57, <http://dx.doi.org/10.1016/j.media.2014.08.002>.
 - [14] Azzopardi G, Petkov N. Automatic detection of vascular bifurcations in segmented retinal images using trainable COSFIRE filters. *Pattern Recogn Lett* 2013;34(8):922–33.
 - [15] Azzopardi G, Petkov N. A shape descriptor based on trainable COSFIRE filters for the recognition of handwritten digits. In: *Proceedings of Part II Computer Analysis of Images and Patterns – 15th International Conference, CAIP 2013*. 2013. p. 9–16, http://dx.doi.org/10.1007/978-3-642-40246-3_2.
 - [16] Azzopardi G, Fernández-Robles L, Alegre E, Petkov N. Increased generalization capability of trainable cosfire filters with application to machine vision. In: *24th International Conference on Pattern Recognition, ICPR 2016*. 2016. p. 279–91.
 - [17] Azzopardi G, Petkov N. Ventral-stream-like shape representation: from pixel intensity values to trainable object-selective COSFIRE models. *Front Comput Neurosci* 2014;00080, <http://dx.doi.org/10.3389/fncom.2014>.
 - [18] Dutta S, Pal S, Mukhopadhyay S, Sen R. Application of digital image processing in tool condition monitoring: a review. *CIRP J Manuf Sci Technol* 2013;6(3):212–32, <http://dx.doi.org/10.1016/j.cirpj.2013.02.005>.
 - [19] Zuiderveld K. Graphics gems iv. In: Heckbert PS, editor. *Contrast Limited Adaptive Histogram Equalization*. San Diego, CA, USA: Academic Press Professional, Inc.; 1994. p. 474–85.
 - [20] Petkov N, Wieling M. Gabor Filter for Image Processing and Computer Vision; 2008 <http://matlabserver.cs.rug.nl/edgedetectionweb/index.html>.
 - [21] Grigorescu C, Petkov N, Westenberg MA. The role of non-CRF inhibition in contour detection. In: *The 11-th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision*; 2003.
 - [22] Grigorescu S, Petkov N, Kruizinga P. Comparison of texture features based on Gabor filters. *IEEE Trans Image Process* 2002;11(10):1160–7, <http://dx.doi.org/10.1109/TIP.2002.804262>.
 - [23] Kruizinga P, Petkov N. Nonlinear operator for oriented texture. *IEEE Trans Image Process* 1999;8(10):1395–407, <http://dx.doi.org/10.1109/83.791965>.
 - [24] Petkov N. Biologically motivated computationally intensive approaches to image pattern recognition. *Future Gen Comput Syst* 1995;11(4–5):451–65, [http://dx.doi.org/10.1016/0167-739X\(95\)00015-K](http://dx.doi.org/10.1016/0167-739X(95)00015-K).
 - [25] Petkov N, Kruizinga P. Computational models of visual neurons specialised in the detection of periodic and aperiodic oriented visual stimuli: bar and grating cells. *Biol Cybern* 1997;76(2):83–96.
 - [26] Petkov N, Westenberg MA. Suppression of contour perception by band-limited noise and its relation to nonclassical receptive field inhibition. *Biol Cybern* 2003;88(3):236–46, <http://dx.doi.org/10.1007/s00422-002-0378-2>.
- Laura Fernández-Robles** received the B.Sc. (2009) degree in Industrial Engineering from University of León where she graduated with honours (First class). In 2011, she received the M.Sc. degree in Intelligent Systems in Engineering at University of León and in 2016 the Ph.D. degree from University of León, Spain and from University of Groningen, the Netherlands. In the present, she is an assistant lecturer and researcher at University of León. Her current research interests include computer vision, pattern recognition and machine learning mainly in industrial environments, but also in medical applications and crime control and prevention.
- George Azzopardi** received Ph.D. cum laude (2013) in Computer Science from the University of Groningen, the Netherlands. Before his Ph.D., he earned his B.Sc. and M.Sc. degrees in Computer Science from Goldsmiths and Queen Mary University of London, respectively. In 2015 he joined the University of Malta as a lecturer and kept affiliation with the University of Groningen. He is a co-editor of the CAIP2015 conference proceedings and a co-chair of the first international workshop on computational models of the visual cortex (CMVC). His current research interests are in the fields of signal processing, pattern recognition, brain-inspired computer vision and machine learning, and has published articles in several journals.
- Enrique Alegre** received the M.Sc. degree in Electrical Engineering in 1994 from the University of Cantabria and the Ph.D. degree in 2000 from the University of León. Currently, he is an Associate Professor in the Department of Electrical, Systems and Automation, University of León, Spain. His research interests include computer vision and pattern recognition applications to medical and industrial problems, and more recently, machine learning and image processing applications for crime control and prevention.
- Nicolai Petkov** received the Dr.sc.techn. degree in computer engineering from Dresden University of Technology, Germany. He is a professor of computer science and head of the Intelligent Systems Group of the Johann Bernoulli Institute of Mathematics and Computer Science of the University of Groningen, The Netherlands. He is the author of two monographs and coauthor of another book on parallel computing, holds four patents, and has authored more than 100 scientific papers. His current research is in image processing, computer vision, and pattern recognition, and includes computer simulations of the visual system of the brain, brain-inspired computing and computer applications in health care.
- Manuel Castejón-Limas** is Assistant Professor at University of León. His research interests are focused on applying data-driven approaches to quality optimization and processes modelling. His past experiences in applying optimization techniques to industry related problems in the steel-making area lead to the implementation of robust predictive models on hot dip galvanising lines and steel annealing furnaces as well as predictive systems for steel coils cleaning systems and the determination of mechanical properties of the final product. In the automotive industry, he has applied these techniques to equally improved the quality of rubber extrusion processes by the deployment of a data-driven manufacturing support system.