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VISION SYSTEM FOR DIAGNOSTIC TASK

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ABSTRACT

Our problem is a diagnostic task. Due to environment degraded conditions, direct measurements are not possible. Due to the rapidity of the machine, human intervention is not possible in case of position fault. So, an oriented vision solution is proposed. The problem must be solved for high velocity industrial tooling machines. Degraded conditions: vibrations, water and chip of metal projections, dazzling..., are present all the time. Image analysis in constraint environment depends on constraint importance. Before tooling, the vision system has to answer: "is it the right piece at the right place?" Complementary methods presented in this paper are proposed in an adaptive way to solve this diagnostic problem. This detection is made by comparing an acquired camera image of the piece to be tooled with an image of reference. Some image processing methods are performed and combined in order to extract 2D features. Some of these 2D features are evaluated and used as parameters in a diagnostic process. After a data analysis, image parameters are reduced. First, we present an overview of image processing methods generally used to solve that kind of problem and their limitations in our particular degraded case. In order to obtain automatic and robust classification, two methods are implemented. The first one is based on Bayes technique that provides a good classification in case of fault presence. The second method is based on neural networks and provides good results in case of images without faults. These two methods give a global rate of good classification greater than 90%, for 720 images acquired from an industrial site.

KEYWORDS: Diagnostic task, 2D Vision, Video camera, Image matching, Bayes classifier, Neural classifier,

INTRODUCTION

Image analysis in constraint environment depends, of course, on constraint importance. Our problem must be solved for high velocity industrial tooling machines. So vibrations, water and chip of metal projections, dazzling, are present all the time. In this case, only one method cannot achieve a diagnostic problem: is it the right piece at the right place?
That problem can be solved in a 3D way, superimposing a known virtual model onto the image and finding the 3D real position of the object like MORSE presented by Mundy(Mundy, et al, 1995) using a multi image system or using a multi image system or FCRG(Fuzzy Conditional Rule Generation) presented by McCane(Mc Cane, 1996) using a stereo based system. On the same problem we tried a 2D/3D approach (Triboulet, et al, 2001) which gave good results. Those methods are time consuming. Using only 2D information seems then more efficient. We present this approach in the following lines.
First part presents an overview of image processing methods generally used to solve that kind of problem and their limitations in our particular degraded case. Second part presents our choice with complementary approaches using three image parameters. Third part presents the self adaptive approach with experimental conditions and results. Finally, conclusion and future works are set out.

Oriented vision analysis is a well-known technique in industrial environment because work conditions are supposed to be well known. On this assumption, work environment can be controlled to achieve in a correct way a diagnostic task. It is not possible with high velocity tooling machines. Due to strong constraints as vibrations, water and chip of metal projections, dazzling, and the solution is not so simple.

THE DIAGNOSTIC PROBLEM: IMAGE ANALYSIS SOLUTIONS

The problem is to know, before a machining task begins, if the right piece (cylinder head, crankcase ...) is on the right place and also if no manufacturing faults are present.

Image pre-processing.

Pre-processing is a signal analysis problem: finding intensity rated levels of all areas using filtering. To eliminate noise without making edges worse, a method using a smoothing filter and an enhancement filter can be implemented using the functions:

$$f_x(x,y) = \eta x e^{-\alpha|x|}.(\alpha|y|+1)e^{-\alpha|y|}\text{............}(1)$$

$$f_y(x,y) = \eta x e^{-\alpha|y|}.(\alpha|x|+1)e^{-\alpha|x|}\text{............}(2)$$

Where η is normalization constant and α is a parameter and where *(x,y)* are pixel image coordinates. A Gaussian filter is currently used for its isotropic and separating properties. Koenderink (Koenderink, 1984) did it in a spatial domain using a convolution filter. It can also be done in a spectral domain (Florack, et al, 1994) or using a recursive way of implementation like in Deriche and Giraudon (1991), Deriche and Giraudon (1992) and Deriche and Faugeras (1995)

Structural primitives extraction

For relevant information like line segments or arc of circles, edge extraction followed by a polygonal approximation can be done. The majority of the developed techniques are using local

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derivation operators of first or second order. Then, respectively, a research of local maxima or zero crossing is done.

Another approach can be done using a derivative method based upon gradient operation (Shen and Castan, 1986). An optimization criterion is implemented taking into account a pre defined model of the edge to be detected. Gradient approximation is obtained using Deriche optimal derivation filter (Deriche, 1987). Based upon Canny's formalism (Canny, 1986), the hysteresis filter guarantees three performance criteria: (1) good detection, (2) good localization and (3) uniqueness of the solution. Image gradient is obtained by convolution of the original image with a filter. An important fact is that to reduce Computer Processing Unit(CPU) time consuming, this algorithm is recursively implemented.

Then local maxima are extracted from the gradient norm in the gradient direction and a hysteresis threshold is applied to improve edge extraction. Polygonal approximation by Pavlidis (1977) leads to a set of segments and arc of circles.

High curvature points

This part presents a method used to extract high curvature points. Such extractors were studied by Smith & Brady (Smith and Brady, 1995). Another one presented by Harris(Harris and Stephens, 1988) is a modification of the corner detector implemented by Morravec (Moravec, 1977). This filter is better for detection than the others presented above and is particularly robust to noise due to image compression and to camera movement with respect to the scene.

COMPLEMENTARY METHODS

In the tooling machine degraded environment, image processing is presented in Figure 1 and is the same for the reference object and each new object. Image smoothing and enhancement are done using Deriche and Shen filters. Edges and polygonal approximation are obtained through Deriche(1987) and Pavlidis(1977) methods. High curvature points are obtained with Harris(1988).

Then, three correlation rates are built between images of the reference object and images of the new object.

- high curvature points correlation HCPC,
- segments correlation SegC (after polygonal approximation),
- gray level correlation GLC.

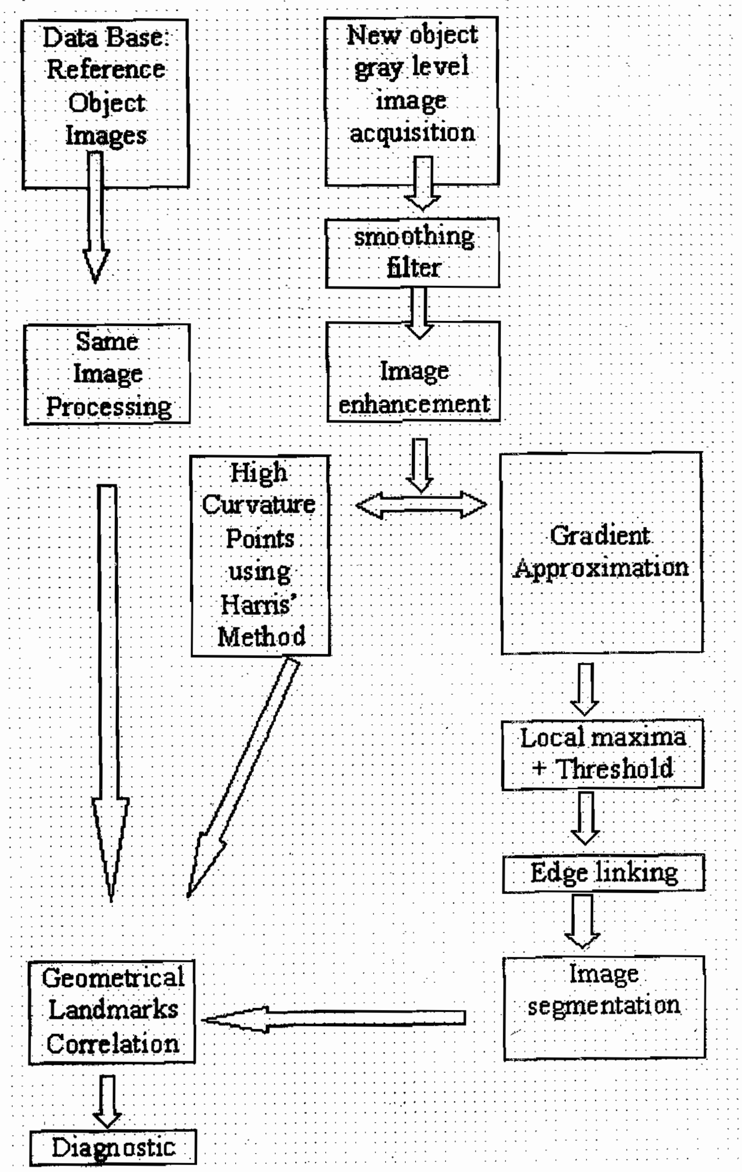

Figure 1: Image analysis method

For the two first correlation rates, a matching is done between high curvature points or segments. The third correlation rate gives a gray level similarity calculated with the inter correlation factor. Figure 2 shows image analysis results on a part of a cylinder head.

We use the analysis method presented(figure1) to compare a reference image to an image of the same kind of object with a failure. Image size presented in figure 2 is 170x220 pixels.

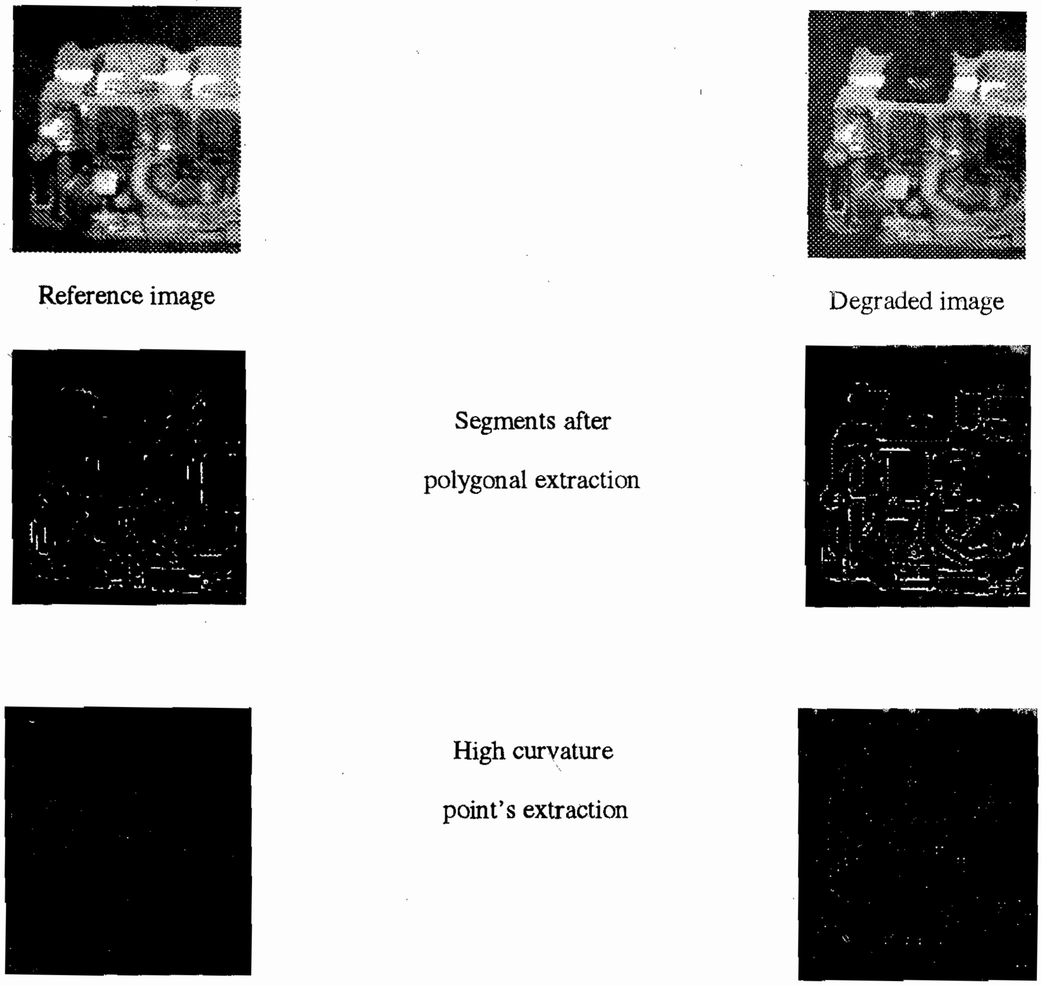

Figure 2: Image analysis results

Self adaptive approach

Now, the way image parameters are calculated is known. Our aim is to use those parameters to obtain a reliable answer in the diagnostic process. Using different parameters is really important because we can face very different situations on the object: defaults, position errors, light variation... We proceed in more ways than one. First an operating way is defined. Second, the performances of the three parameters HCPC, SegC and GLC are tested, individually then associating two of them and finally associating the three parameters simultaneously. Third, this work is completed by a principal component analysis to test the relevance and the correlation of those parameters. Fourth, we define fifteen new parameters. Fifth, another principal component analysis is done to select the most relevant parameters. Sixthly, as an empiric rule was difficult to find to combine those parameters, we have tested two approaches: One using bayesian method and the second using neural method. We have encouraging results. Those results show that it is possible to find a solution in image comparison. It is obtained grouping results given by different image analysis methods.

Operating mode definition

The general setting for this study is industrial mechanical parts analysis. We must compare an object to a reference object and then decide if they are identical. This notion includes the lack of defaults and the same position as the reference. In fact, we must control a tooling process. So this process cannot be started if initial conditions are not correct. So, we worked with 20 images from a cylinder head. Each image is devised in 36 sub images (128 x 96 pixels each). Then, we can work with a set of 720 sub images. For each sub image, we are able to take a decision in comparison with a reference sub image.

This set was devised in two classes.

- Class "0" represents sub images which are different from the reference. 146 sub images are ordered in this class. Differences are defaults, metal turnings or small position errors.
- Class "1" represents sub images which are the same as the reference. 574 sub images have been ordered in this class.

Figures 3 and 4 represent two samples of the image database. Image (a) is the reference. Image (b) has no default so belongs to the Class "1". Image (c) has a default so belongs to the Class "0".

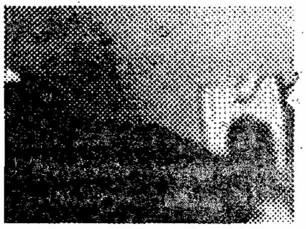

Figure 3-a : reference

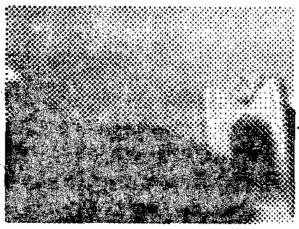

Figure 3-b : image without default

Figure 3-c : image with default

Figure 4-a : reference

Figure 4-b : image without default

Figure 4-c : image with default

Figures 3 and 4 : Images from the data set

On images 3-c and 4-c defaults are turnings of metal. It is about a few pixels in the image. So to detect a difference from the reference images the parameters must be robust and the decision rules reliable enough.

Evaluation of the three initial parameters

The three parameters presented must find the similarity of two images using High Curvature Points (HCPC), segments (SegC) and Gray Level Correlation (GLC). We must find a rule using those three parameters delivering a decision as: "tested image belongs to Class "0" or Class "1" ". Owning to the fact that this work is in industrial environment, the decision rule must minimize classification errors of the Class "0" toward Class "1". In fact, if the operator is needed even when the object in the tooling machine is on the right place, leads to a loss of time. On the other hand, if we decide the tooling of an imperfect or badly clamped object, leads to serious results on the tooling machine (broken tool). Nevertheless we must maximize the global percentage of good classification. The problem to be solved is a data classification problem which estimators are quantitative parameters. As we got two classes, a priori defined, we want to characterize, it is a controlled classification problem (Diday, et al, 1982).

A first empiric approach has been presented in Merad, et al (2001). Following several observations and discussions with experts, a rule was defined. Then, each of the 720 sub images has been classed using the following decision rule:

If (HCPC>0.9 AND GLC > 0.9) THEN image is assign to Class "1"

ELSEIF (HCPC > 0.8 AND SegC > 0.7 AND GLC > 0.85) THEN image is assigned to Class "1"

ELSE image is assign to Class "0".

Such a rule leads to a global good classification rate greater than 94%. That is quite correct for such an approach. Nevertheless, if Class "1" is well identified (97.85%) it is done to the detriment of Class "0" which 10% of sub images are badly assigned. Then, it is really important to improve those results. It can be done through the behavior analysis of those three parameters.

A first approach was done on the classification results obtained with HCPC, SegC and GLC.

(i) We studied the results given by each parameter alone. The rule was really simple:
IF (Parameter > Threshold) THEN image is assigned to Class "1"
ELSE Image is assigned to Class "0"
The threshold variation was done from 0.49 to 0.99 by 0.1 steps. Then, for each parameter we noted the threshold value the best results.

(ii) Then we used the threshold values of this first test to combine two parameters with a "AND" rule.

(iii) Finally we did a combination of the three parameters.

We calculated a good classification rate for each class of the whole 720 sub images. This rate takes into account numerical disparity of the Class "0". Table I presents those results.

Table I: Exhaustive analysis of parameters: HCPC, SegC and GLC

Case	Threshold values (optimal result)	% good classification	% good classification class "0"	% good classification class "1"
HCPC alone (50 tests)	HCPC ≥ 0.79	94,72%	89.73 %	95.9%
SegC alone (50 tests)	SegC > 0.49	86.53%	38.36%	98.%
GLC alone(50 tests)	GLC > 0.99	93.47%	93.84%	93.38%
HCPC and GLC(561 tests)	HCPC > 0.79 AND GLC > 0.98	94.72%	93.84%	94.9%
HCPC and SegC(2601 tests)	HCPC > 0.79 AND 0.4< SegC <0.45	94.58 %	89.73%	95.82%
GLC and SegC (561 tests)	GLC > 0.99 AND 0.4<SegC<0.45	93.33%	93.84%	93.2%
HCPC and SegC and GLC (26120 tests)	GLC = 0.99 AND 0.5<HCPC< 0.59 AND 0.4<SegC<0.45	93.61%	95.21%	93.2%

Based upon the results of this table, we can see that the rate of good classification is a bit better than the rate of the empirical rule (94.72%). At the same time, the error rate of the Class "0" is reduced to 6%. This result is obtained jointly HCPC and GLC. Then, combining the three parameters brings down the rate of the Class "0" to 5%.
After, we did a principal component analysis on the whole data using HCPC (Var1), SegC (Var2) and GLC (Var3). Results show that 90% of the power is given by two eigen values. It shows the relevance of those parameters. Moreover, F1 axis is constituted by those three parameters with the same ratio. But we can find an important correlation between HCPC and GLC parameters as we can see in the correlation circles presented in Figure 5.

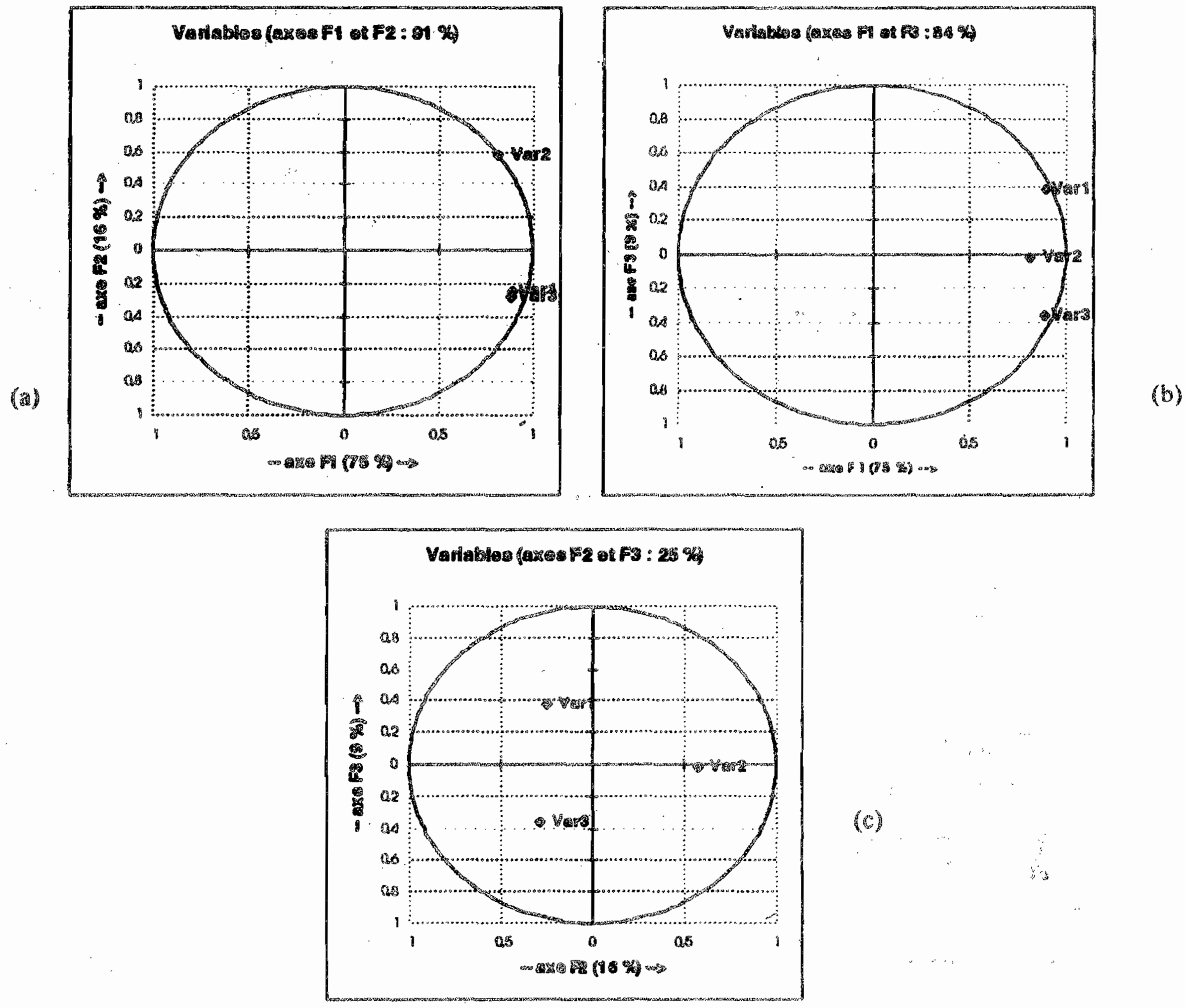

Figure 5: Correlation circles from the principal component analysis(PCA) of the three parameters.

We can remark on those circles, that the SegC parameter has a null contribution for the F3 axis, in opposition to the other parameters. To improve this analysis on the discriminating capacity of those parameters, the principal component analysis was done one more time but separately on Class "0" and on Class "1". Table II presents correlation matrices proceeding from those three analysis.

Those results show that correlation is important between the three parameters. Especially for HCPC and GLC from Class "0". On the other hand, elements from the Class "1" are not in correlation, see Table II. So we can authenticate the choice of those three parameters and their discriminating capacity. Nevertheless, to improve classification results, we must introduce other parameters.

Table II: Correlation matrices from the PCA with three parameters.

	PCA on 720 images			PCA on 146 images Class « 0 »			PCA on 574 images Class « 1 »		
	Var1	*Var2*	*Var3*	*Var1*	*Var2*	*Var3*	*Var1*	*Var2*	*Var3*
Var1	1	**0,581**	**0,728**	1	**0,460**	0,575	1	0,023	0,076
Var2	**0,581**	1	**0,567**	**0,460**	1	0,566	0,023	1	0,057
Var3	**0,728**	**0,567**	1	**0,575**	0,566	1	0,076	0,057	1

Definition of new features

We have analyzed some images that give false results. We saw that some errors were done on images where there was a little number of High Curvature Points (<5) or segments. Actually, if only one of these features is not detected, the value of the coefficient HCPC or SegC is very different. We also [illegible] the difference between some features computed on each image: the reference image and the image to classify. We also introduce some information about lighting using mean and standard deviation of gray levels. All these features are presented in the table III.

We perform again, with these 15 features, a principal component analysis. Now 6 axes are necessary in order to obtain 90% of the energy. On figure 6 we show the correlation circles for the axes F1, F2 and F3. On these circles we see that some variables are very correlated: the pairs (8, 9), (10,11), (12,14) and (13,15). Some other variables are less correlated: (1, 2, 3) or (4, 5, 6, 7). After the PCA on the whole database, we do an other analysis on the 146 images from the class "0" and the 574 images from the class "1". We also see, on these matrices, that HCPC, SegC and GLC have not the same behavior for the two classes, as we notify it in the previous study. It is very interesting because that means they [illegible] power. Now we have to find an [illegible] classify our images. We want to obtain a method without empiric threshold. Generally, the best classifier for a given task can be found by comparing different criteria: classification error, computational complexity and hardware implementation efficiency (Holmström, et al, 1997). We have decided to test two well-known techniques: bayesian technique and neural technique. For these two ways, we have kept seven parameters that we have chosen with respect to the PCA conclusions. There are the seven first parameters in the table III. On figure 6 we see that the variables 1, 2 and 3 are very far from the variables 4, 5, 6 and 7. In the neural technique, we test some others features configuration. We discuss about the different results at the end of this part

Table III: The 15 parameters used for the classification of the images

Name of the parameter	N° PCA	Nature of the parameter
HCPC	Var1	Coefficient computed on the high curvature points
SegC	Var2	Coefficient computed on the segments
GLC	Var3	Correlation coefficient computed on the gray levels
≠HCP	Var4	Difference between the number of high curvature points in the reference image and the image to classify
≠SEG	Var5	Difference between the number of segments in the reference image and the image to classify
≠MEAN	Var6	Difference between the mean of gray levels in the reference image and the image to classify
≠STD	Var7	Difference between the standard deviation of gray levels in the reference image and the image to classify
NHCPC_ref	Var8	Number of high curvature points in the reference image
NHCPC_test	Var9	Number of high curvature points in the image to classify
NSEG_ref	Var10	Number of segments in the reference image
NSEG_test	Var11	Number of segments in the image to classify
MEAN_test	Var12	Mean of gray levels of the image to classify
STD_test	Var13	Standard deviation of gray levels of the image to classify
MEAN_ref	Var14	Mean of gray levels of the reference image
STD_ref	Var15	Standard deviation of gray levels of the reference image

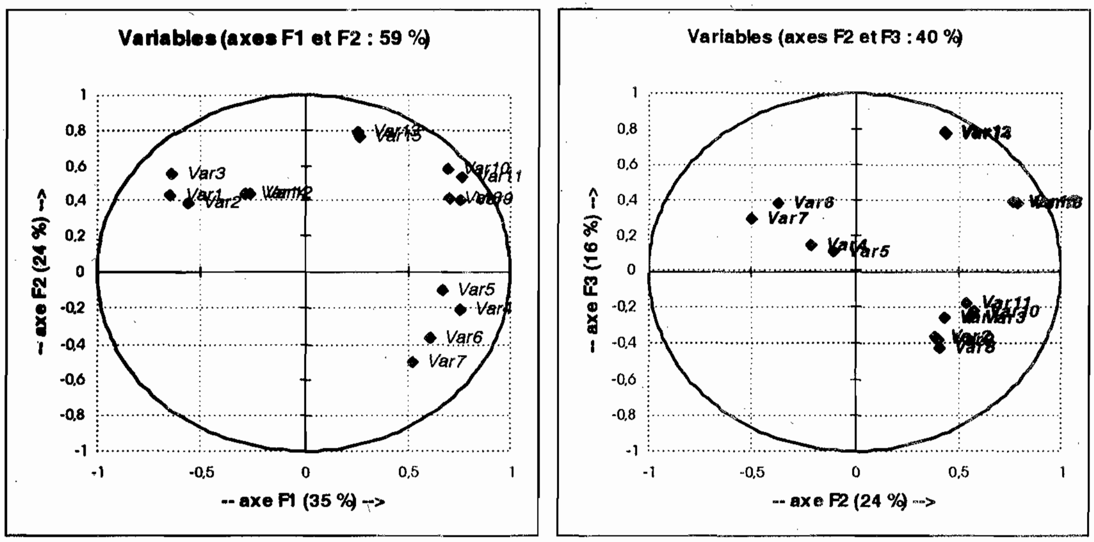

Figure 6: Correlation circles from PCA on the 720 images with 15 parameters.

Bayesian method

We use in this part the seven first variables from table III. We use the Bayes theory as it is exposed by Celeux (Celeux, et al 1989). As we have two classes, we have to define two values (C_{01} and C_{10}) which represent the bad classification costs for one class in the other class. For choosing these values, we have done a great number of tests and we keep the values that provide the best classification rate. In table IV we present the results we obtained.

Table IV: Result of bayesian classification with 7 parameters

With the aim:	C_{01}	C_{10}	*Rate of good classification class « 0 »*	*Rate of good classification class « 1 »*	*Rate of global good classification*
Class « 0 » maximum	3 to 3,3	0,1	93,84 %	95,82 %	95,42 %
Class « 1 » maximum	0,1	> 9,6	86,99 %	98,43 %	96,11 %
Global rate maximum	0,1	1,7 to 3,3	88,36 %	98,26 %	96,25 %

These results are not very far from those of table I but we see some improvements. Actually, with the hypothesis to obtain the maximum rate of global good classification with the minimum rate of classification error for the class "0", we have a global good classification rate that is over 95% (line 1 of table IV). It is an encouraging result but we hope it is possible to increase the good classification rate in the class "0".

Neural method

We want to know which rate of good classification it is possible to obtain by using a neural network for doing an automatic classification of our data. We use the next hypothesis: the network is a multilayer perceptron (MLP) with one hidden layer (Ripley, 1996), (Haykin, 1999). We have devised the set of data in three sets: one learning set with 360 images, one validation set with 180 images and one generalization set also with 180 images. We have tested different numbers of parameters. First we have worked with the seven previous variables. Then we have tried to increase the rate of good classification with other parameters like 8 and 10, then with the first eleven parameters from table I. In the end, we use the whole set of parameters. For each set of variables, we perform one hundred tests on the 180 images of the generalization set. The results which are shown in table V are the mean of these 100 tests. We also look for the best number of neurons.

Table V: Results of neural technique with different numbers of features.

Number of parameters	7 variables	9 variables	11 variables	15 variables
Number of neurons	2 neurons	1 neuron	1 neuron	1 neuron
% of good classification class « 0 »	89,78	91,45	92,41	89,79
% of good classification class « 1 »	98,81	98,45	98,37	98,27
% of global good classification	96,98	97,03	97,16	96,55

In table V, we see that the neural technique allows us to increase the rate of good classification for the image from the class "1", and also the global good classification rate. But the rate of good classification for the class "0" is under the results provided by the bayesian technique. We can also see that we do not increase the results when we add some variables. Even the results with 15 parameters are below the results with 11 parameters. The best results are obtained with 11 features on each image. One or two neurons are sufficient for the hidden layer. That means the classification rule is almost linear.

IV.7. Comparison of bayesian and neural techniques

We want to obtain an automatic classification that is the more sturdy as possible. The bayesian technique provides a good classification for the class "0". The neural technique is better for the class "1". So we have studied the complementarity between the results from these two techniques. In an other work (Loaiza, et al, 2001), we have done the same thing and we obtained very good results. For this analyze we compare, one by one, the answer given by each of the two methods for the 720 images. We use 7 parameters for the two methods. Table VI presents the results (bayesian result are the same as in table IV).

Table VI: Comparison of the results given by neural and bayesian techniques (on 720 images and with 7 parameters)

Methods	Neural(2 neurons)	Bayesian
% class "0"	92,47%	93,83%
% class "1"	97,04%	95,82%
% global	96,11%	95,42%

The bayesian method makes 33 mistakes (9 for the class "0" and 24 for the class "1") and the neural technique makes 29 mistakes (11 for the class "0" and 17 for the class "1"). For only 12 images, the two methods give the same answer. So, for 3% of the data, the answer of the neural method is true and each one of the bayesian method is false. It is the contrary for 2% of the data. If we use this disparity between the two methods, it is possible to increase the rate of good classification for each class. Expecting results are shown in table VII. The problem is to find a rule combining the two techniques. Some works have been done in this way (Loaiza, et al, 2001), (Kittler, et al, 1998) and we have to test it again.

Table VII: Combination of two classifiers. Expecting results for the example.

	Rate of good classification
% class « 0 »	95,2%
% class « 1 »	99,13%
% global	98,33%

CONCLUSION

In this paper, we have presented and evaluated some methods devoted to a vision system for high velocity tooling machines. Due to the rapidity of the machine, human operator intervention is not possible in case of object pose fault. Before tooling the vision system has to answer: "is it the right piece at the right place?" This detection is made by comparing an acquired camera image of the piece to be tooled with an image of reference.

Vision conditions are degraded due to vibrations, water and chip of metal projections,...Then some image processing methods are performed and combined in order to extract 2D features. Some of these 2D features are evaluated and used as parameters in a diagnostic process. In order to obtain automatic and robust classification, two methods are implemented. The first one is based on Bayes technique that provides a good classification in case of fault presence. The second method is based on neural networks and provides good results in case of images without faults. These two methods give a global rate of good classification greater than 90%, for 720 images acquired from an industrial site.

As further work, we plane to study the combination of these techniques in order to improve the image classification results.

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