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Naïve Screw Nut Classifier Based on Hu's Moment Invariants and Minimum Distance

Antonio Alarcón-Paredes, Roberto Contreras-Garibay,
Gustavo Adolfo Alonso-Silverio and Eric Rodríguez-Peralta

Abstract—**In this paper, an algorithm for classification of screw nuts by means of digital image processing is presented. This work is part of a project where a production line was built, and is focused on the quality assessment section. The algorithm presented classifies among good and poor quality screw nuts passing by a conveyor belt, by computing Hu's moment invariants of its picture. Those moment invariants are the input of a minimum distance classifier, obtaining very competitive results compared with some other classification algorithms of the WEKA plattform.**

Index Terms—**Classification algorithms, Computer vision, Manufacturing automation, Pattern recognition.**

I. Introduction

The computer vision techniques have been developed since 1960's, and continued growing as in theory and applications [1], [2]. Nowadays, these techniques are used in a wide range of applications, such as medical imaging [3]-[5], industry automation [6], [7], monitoring [8], food quality [9]-[11], quality assessment [12], [13], among others [14], [15]. The product quality depends on how the industry processes are performed. A systematic inspection of these tasks have been usually done by humans, however, in some cases they could incur in errors due to fatigue and psychological or health factors; these errors make a computer vision system more attractive [16], [17].

With the increasing volume production, it is necessary to create strategies to achieve quality products at large scale in less time. For that reason, manufacturing companies have chosen computer vision automation as the solution of the problem established above [18].

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A. Alarcón-Paredes is with the Universidad Autónoma de Guerrero, Chilpancingo, Guerrero. 39060 México (e-mail: aalarcon@uagro.mx).

J. R. Contreras-Garibay, is Computer Engineer from the Universidad Autónoma de Guerrero, Chilpancingo, Guerrero. 39060, México (e-mail: jroberto@hotmail.com).

G. A. Alonso-Silverio is with the Universidad Autónoma de Guerrero, Chilpancingo, Guerrero. 39060 México (corresponding author to provide phone: +5217471122838; e-mail: (gsilverio@uagro.mx).

E. Rodríguez-Peralta is with the Universidad Autónoma de Guerrero, Chilpancingo, Guerrero, 39060 México (e-mail: erodriguez@uagro.mx).

Automation is a key factor to improve the production lines in order to stay alive in the competitive production market. For this reason, an automatic system for object inspection could be implemented on the quality assessment in industry.

The main idea is that a computer vision system performs the following whole process: from image acquisition, feature extraction and image analysis, to finally classify among good and poor quality objects [19].

In this paper, a computer vision system for nut quality control in industry is presented. This system is former part of a project where a conveyor belt built with Lego Mindstorms NXT kit is used [20], however, this work focuses only in the quality assessment part.

The proposed algorithm classifies between good and bad quality nuts. For its classification, the system takes a picture of a nut passing by a conveyor belt, applies some preprocessing to the image, and then computes the Hu's moment invariants [21]. The values of the seven moments constitute the input data to the algorithm, which is a minimum distance classifier, and uses the Euclidian distance [22].

The results obtained with the proposed algorithm are very competitive with a variety of classification algorithms included in the WEKA open source platform [23].

II. Theoretical Support

A. Image acquisition

One of the main problems when acquiring an image is the different lighting and brightness condition of the environment, since a proper light permits to obtain a good quality image [24]. Here, that issue is simply solved by using a light-controlled chamber, with infrared sensors and a webcam placed within.

In order to take the pictures of the nuts, the system uses the infrared sensors placed beside the conveyor belt; once the sensors detect and object passing by, the webcam automatically receive a signal to take an RGB color picture.

Once the image is stored, it is cropped into a specific area; the boundaries of this area were chosen in an experimental way, and the nut is always into this area. The cropped image is now converted to a gray scale image. The latter steps help

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the image processing to be more efficient.

B. *Spatial filtering*

In general, spatial filtering of an image $f(x,y)$ of size $M \times N$ with a filter mask $h(s,t)$ of size $m \times n$ is given by the expression:

$$g(x,y) = \sum_{s=0}^{m-1} \sum_{t=0}^{n-1} f(x+s, y+t) h(s,t) \quad (1)$$

where $x = 0,1,\dots,M-1$ and $y = 0,1,\dots,N-1$.

In this work, the expression (1) and a Gaussian mask are used to smooth the image and for noise reduction. The next step consists in obtain the Sobel gradient ∇f of the image by means of the components *Gx* and *Gy*, computed using (1) and the *x*-direction and *y*-direction Sobel masks.

C. *Feature extraction and Hu's moment invariants*

In [3]-[16], the feature extraction process is divided into different steps, and a variety of algorithms for this purpose and some other transformations are used, such as the conversion to other color spaces than RGB, the FFT, PSO, PCA, Markov Chains, Kalman filters, Canny edge detector, among others. The work presented in this paper is called a *naïve classifier*, since instead of using complex algorithms for feature extraction, uses a simple preprocessing for noise reduction, the image gradient, and then, Hu's moment invariants are obtained. These moments could be computed as follows:

The two-dimensional (*p*+*q*)th order moment are given by:

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x,y) \quad (2)$$

where $p,q = 0,1,2,3,\dots$

Some invariant features can be achieved using the central moments, which are computed with the following equation:

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \quad (3)$$

where $\bar{x} = \frac{m_{10}}{m_{00}}$, $\bar{y} = \frac{m_{01}}{m_{00}}$, and the point $(\bar{x},\bar{y})$ is the centroid of the image $f(x,y)$.

Scale invariance could be obtained by normalization. Thus, the normalized moments are described by

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}} \quad (4)$$

Finally, by means of (2), (3), and (4), the seven Hu's moment invariants are computed as follows:

$$\phi_1 = \eta_{20} + \eta_{02} \quad (5)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2 \quad (6)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (7)$$

$$\phi_4 = (\eta_{30} - \eta_{12})^2 + (\eta_{21} - \eta_{03})^2 \quad (8)$$

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12}) - 3(\eta_{21} + \eta_{03})^2\right] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})\right] \quad (9)$$

$$\phi_6 = (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] + 4\eta_{11}(\eta_{30} - \eta_{12})(\eta_{21} + \eta_{03}) \quad (10)$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \quad (11)$$

The Hu's moment of all the training images are obtained and used to train the algorithm, such that each image can be represented by a seven-dimensional vector, *i.e.*, the value of the seven moment invariants. The patterns which represent the training images are stored into a *comma separated values* (.CSV) text file in order to be used by the proposed algorithm; these patterns are also stored in an .ARFF file, this file is used by the WEKA data mining software.

D. *Fundamental set of patterns*

In this stage it becomes necessary to obtain the algorithm training set. Let the input patterns be represented by column vectors **x** of size *n*, and the associated class is represented by c, with $c \in \{0,1\}$ since there are only two output classes: good quality nuts or poor quality nuts. Each input pattern $\mathbf{x}^k$ is corresponded to one and only one output class c^k forming thus the association of the ordered pair: $(\mathbf{x}^k, c^k)$. The set of p associations of input patterns $\{(\mathbf{x}^1,c^1),(\mathbf{x}^2,c^2),\dots,(\mathbf{x}^p,c^p)\}$ is called the fundamental set, and is represented as

$$\{(\mathbf{x}^k, c^k) \mid k = 1,2,\dots,p\} \quad (12)$$

E. *Euclidian distance*

For measuring similarity between patterns, the Euclidian

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distance is used as follows:

$$d\left(\mathbf{x}^{\omega},\mathbf{x}^{k}\right)=\left[\sum_{i=1}^{n}\left|x_i^{\omega}-x_i^{k}\right|^2\right]^{\frac{1}{2}} \tag{13}$$

Note that to obtain the minimum distance, the use of the squared Euclidian distance is sufficient, thus:

$$d^2\left(\mathbf{x}^{\omega},\mathbf{x}^{k}\right)=\sum_{i=1}^{n}\left|x_i^{\omega}-x_i^{k}\right|^2 \tag{14}$$

III. Classification Algorithm

The proposed algorithm is described as follows:

1) Obtain an RGB picture of the nut in the conveyor belt (Fig. 1).
2) Crop the image for efficiency and obtain the gray level image of the nut, as shown in Fig 2.
3) In Fig. 3, the noise reduction of the image by means of a Gaussian filter is shown.
4) Obtain the Sobel gradient of the filtered image resulting in previous step (See Fig. 4).
5) Get the seven Hu's moment invariants as established in equations (5) to (11). From now, these moments may be referred as patterns, or image patterns.

Fig. 1. RGB image acquired with a conventional webcam.

6) Compute the distance vector dv of size p (the same as the cardinality of the fundamental set) with the Euclidian distance between the test image patterns and each of the training patterns:

$$dv_k = d^2\left(\mathbf{x}^{\omega},\mathbf{x}^{k}\right) \tag{15}$$

$$dv_k = \sum_{i=1}^{n}\left|x_i^{\omega}-x_i^{k}\right|^2 \tag{16}$$

where $\mathbf{x}^{\omega}$ is the pattern of an unknown image, $\mathbf{x}^{k}$ are the p patterns in the fundamental set, and $k=1,2,...,p$. The distance vector is then normalized.

7) It is necessary to choose a classification threshold denoted by θ, *i.e.*, the greater distance that could exist between two patterns of the same class. This value, which can go from 0 to 1 due to the normalization of vector dv, was obtained by experimentation and varies when the cardinality of the fundamental set changes.
8) Look for the smallest value in the distance vector dv:

$$\varepsilon = \min_i\left(dv_i\right) \tag{17}$$

9) Obtain the class c^{ω} for the correspondent pattern $\mathbf{x}^{\omega}$:

$$c^{\omega}=\begin{cases}1 & \text{if } \varepsilon \le \theta \\ 0 & \text{other case}\end{cases} \tag{18}$$

where a value of $c^{\omega}=1$ represents that the nut is a good quality one; otherwise, means that the object in the image could be a poor quality nut or even a strange object.

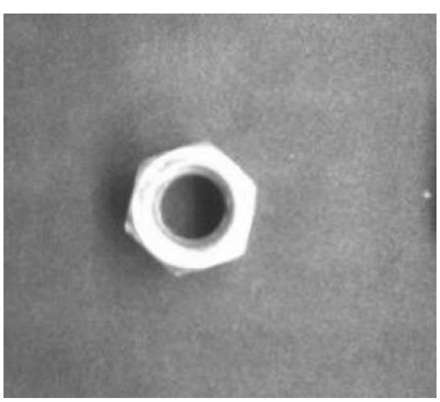

Fig. 2. Cropped grayscale image.

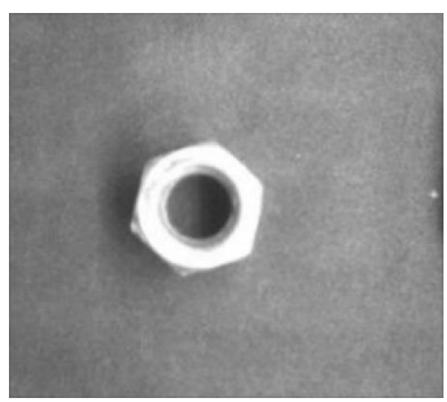

Fig. 3. The image in the Fig. 2 filtered with a gaussian.

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TABLE I
CLASSIFICATION OF THE WHOLE FUNDAMENTAL SET

Classifier	% Performance
Naïve Bayes	84.67%
Bayes Net	87.33%
Logistic Regression	94.67%
Simple Logistic	94.00%
1-NN	**100.00%**
3-NN	96.67%
5-NN	96.67%
AdaBoostM1	99.33%
LogitBoost	97.33%
Bagging	96.67%
PART	99.33%
C4.5	98.67%
Proposed	**100.00**%
AVERAGE	95.80 %

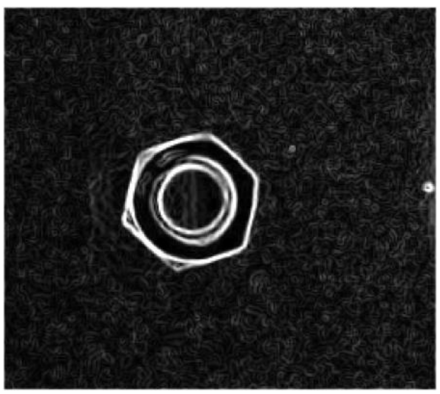

Fig. 4. Image gradient obtained by means of Sobel filter.

IV. RESULTS AND DISCUSSION

A. Preliminars

The proposed algorithm was developed using MATLAB R2013b. A total of 100 pictures of good quality nuts, and 50 poor quality nuts were obtained; all of them were taken on the conveyor belt running.

When speaking of distance function-based classification, it is inevitable to talk about the k-Nearest Neghbours [25], which is a non-parametric *lazy* algorithm. In this paper, the proposed algorithm depends on two principal factors: the first is the cardinality p of fundamental set, *i.e.*, the number of good quality nuts to be compared with nuts to classify, and secondly the similarity threshold θ between the training patterns and the unknown ones. For this reason, a comparative study with different number of p is presented. Although, we run an exhaustive procedure to find the optimal threshold θ for each different value of p. This procedure is carried on only once just when the value of p changes, and can be seen as a system *calibration* process.

TABLE II
RESULTS OF PROPOSED ALGORITHM

p (% hold out)	θ	% Performance
5 (3.33%)	0.85	89.65%
10 (6.67%)	0.68	90.71%
20 (13.33%)	0.59	90.77%
30 (20.00%)	0.46	90.00%
40 (26.67%)	0.40	89.10%
50 (33.33%)	0.35	91.00%

Please note that the distances computed and stored in the distance vector dv are normalized, so the exhaustive procedure must only find values of θ between 0 and 1, which makes this process run faster than it seems.

B. Results classifying the whole fundamental set

The first estimate of the algorithm performance was made by learning and classifying the whole fundamental set entirely.

The WEKA platform was chosen to compare the proposed algorithm with some other classifiers on the state of the art. The classifiers selected were: Naïve Bayes, Bayes Net, Logistic Regression, Simple Logistic, k-NN ($k = 1, 3, 5$), AdaBoostM1, LogitBoost, Bagging, PART, and C4.5.

The process was applied to the proposed algorithm and to 10 classifiers included in WEKA. Results show that only the proposed classifier and the 1-NN can classify the whole fundamental set without ambiguity, *i.e.*, they classify the 100% of patterns.

Table I shows the results of classification with proposed algorithm and the other 10 selected algorithms.

C. Comparison between algorithm proposed and WEKA algorithms.

The second estimation of the performance was carried out by learning 5 patterns and classifying 145, then learn 10 and classify 140, learn 20 and classify 130, learn 30 and classify 120, learn 40 and classify 110, and finally learn 50 and classify the other 100.

Since the proposed algorithm was tested with different values of *p*: 5, 10, 20, 30, 40 and 50, also needs different values of the threshold θ which were: 0.85, 0.68, 0.59, 0.46, 0.4 and 0.35, respectively.

The election of the *p* nut pictures was done randomly, and takes only good quality ones. Notice that the value of *p* is inversely proportional to the threshold. It means that if there are few nuts to compare with, the algorithm must give a greater margin of similarity between patterns; but if there are many nuts to compare, should give a lower threshold value.

Remember that there are 150 nuts pictures in total, the first 100 are good quality nuts, and the other 50 are poor quality

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TABLE III
COMPARISON BETWEEN PROPOSED ALGORITHM AND SOME OF THE WEKA CLASSIFIERS, USING HOLD-OUT

Classifier	Performance of the classifier using different values for *p* (% of hold-out partitions)					
	p=5 (3.33%)	*p*=10 (6.67%)	*p*=20 (13.33%)	*p*=30 (20.00%)	*p*=40 (26.67%)	*p*=50 (33.33%)
Naïve Bayes	**90.34%**	81.43%	*90.77%*	80.00%	89.09%	76.00%
Bayes Net	82.07%	**92.14%**	88.46%	**90.00%**	88.18%	***94.00%***
Logistic Regression	85.52%	**92.86%**	***93.85%***	88.33%	**91.82%**	87.00%
Simple Logistic	85.52%	86.43%	**92.31%**	85.00%	**91.82%**	***93.00%***
1-NN	86.21%	***96.43%***	**96.15%**	**91.67%**	**91.82%**	91.00%
3-NN	**90.34%**	86.43%	84.62%	84.17%	**92.73%**	***95.00%***
5-NN	66.90%	78.57%	86.15%	84.17%	**92.73%**	***95.00%***
AdaBoostM1	**86.90%**	88.57%	87.69%	86.67%	***90.91%***	88.00%
LogitBoost	**86.90%**	88.57%	87.69%	86.67%	***90.91%***	90.00%
Bagging	66.90%	90.71%	90.00%	**90.83%**	88.18%	*91.00%*
PART	77.93%	87.14%	86.15%	85.00%	90.00%	*92.00%*
C4.5	77.93%	87.14%	86.15%	85.00%	90.00%	*92.00%*
Proposed	**89.65%**	90.71%	90.77%	**90.00%**	89.10%	*91.00%*
AVERAGE	82.55 %	88.24%	89.29%	86.73%	*90.56%*	90.38%

ones. Nevertheless, the algorithm is trained with the *p* patterns in fundamental set, and tries to classify the other 150-*p* patterns; this constitutes a hold out cross-validation algorithm. The performance of the algorithm can be seen in Table II.

The same process was applied to 10 other algorithms in the WEKA platform to be compared with the proposed algorithm. The classifiers selected were: Naïve Bayes, Bayes Net, Logistic Regression, Simple Logistic, k-NN ($k=1,\ 3,\ 5$), AdaBoostM1, LogitBoost, Bagging, PART, and C4.5. In order to make a good comparison, the classifiers selected were tested using the same hold-out partitions used with the proposed algorithm. The results of this experiment are shown in Table III, in which the values with italic style represent the best performance for the classifier in that row, and the bold style values are the top five performances for that value of *p*.

Notice that the proposed algorithm outperforms the average performance for all cases except the case where *p*=40.

V. CONCLUSION

A naïve classifier based on Hu's moments invariants and minimum distance has been presented.

This classifier was tested and compared to other 10 algorithms in the state of the art which are included in WEKA. The results from Table I to Table III shows that the proposed algorithm overcomes the performance of some well-known algorithms in the literature, such as Naïve Bayes, Logistic Regression, k-NN, C4.5 trees, among others. It is clear that some classifiers present a better performance in some cases, although, the proposed algorithm comes close to their results. This behavior is not strange, since the No Free Luch Theorem [26] shows that when a classifier is very good with some family of problems, may be not so good to others.

However, this drawback can be overcome with the simplicity of the algorithm presented in this work.

It is worth to mention that the proposed algorithm is very competitive among state of the art classifiers, and it is possible to be implemented on industry since it has the possibility to be implemented on a single board computer, such as the Raspberry Pi.

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