



CATTLE MARKS RECOGNITION BY HU AND LEGENDRE INVARIANT MOMENTS

G. Sanchez and M. Rodriguez

Faculty of Engineering, Universidad del Magdalena, Santa Marta, Colombia

E-Mail: gsanchez@unimagdalena.edu.co

ABSTRACT

Animal identification and traceability are important aspects for proper application of measures aimed at prevention and control of the agro-food crisis. Some Latin American countries use the hot branding system for animal identification. This paper proposes a digital image processing method to automate the registration and control process of cattle marks. It allows automating the search and comparison process required for cattle mark uniqueness assurance on a computer assisted system. The proposed method combines Hu invariants moments and Legendre moments to produce a feature vector that permits to reach an adequate recognition process. The proposed method has been tested on a dataset of 100 images. Results show that the method allows discriminating between images reducing ambiguity and ensuring the uniqueness of registered marks. We show the results and make an analysis of system applications.

Keywords: Hu moments, legendre moments, 2D image similarity, process automation.

1. INTRODUCTION

Animal identification and traceability are important aspects in the agro-food industries. In the livestock sector, they improve the effectiveness of animal disease prevention and control policies by keeping information of animal health. Animal identification refers to keeping records on individual animals so that they can be easily tracked from their birth through the marketing chain (Fernandez, 2002), (Greene J, 2010). Individual identification enables traceability, which is the ability to access any or all information relating to the animal under consideration throughout its entire life cycle, by means of recorded identifications (Badiaet al. 2015). Identification and traceability constitute a requirement of the international community in order to obtain export licenses. The different existing approaches to animal traceability vary widely, from the more traditional methods such as hot branding to even the most innovative microchip implantation (Riboet al. 2001), (Cajaet al. 1996) or DNA profiles (Felmeret al. 2006). Currently, there are restrictions for the application of some of these techniques for different reasons: electronic devices entail a risk that could affect consumers through the food chain, while hot branding techniques are rejected by strict measures of animal welfare protection. Despite such restrictions, the traditional hot branding technique constitutes the main strategy for animal identification in the Latin American region.

In Latin America, technological tool developments for animal traceability in the cattle market are poor. Local governments require that the marks be registered. The mark registration procedure consists in bringing the branding iron to local authorities (see Figure 1). The mark is registered by means of a copy of the mark image. Initially, a search is carried out in order to establish

that no similar marks have been previously registered. Since no computational system exists, the searching is done using physical records (see Figure-2).

Since no systematized procedure has been established for the registration process, the search procedure uses scattered, fragmented and not digitalized large data sets. This hampers the efficiency and effectiveness of the process, which depend on the visual capacity of the operator, the degree of deterioration of the physical registration, and the quality and clarity with which the mark was acquired. Additionally, the most important effect is that the uniqueness of the registered mark cannot be guaranteed without applying monitoring and control strategies.

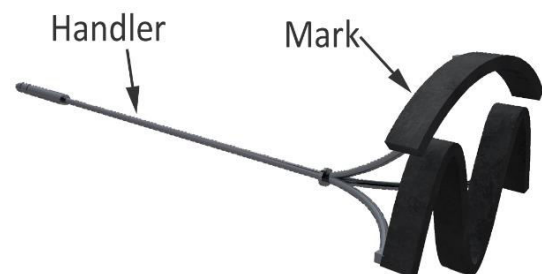


Figure-1. Single character branding iron.

The present study aims to introduce an automatic method for mark registration in marketplaces where hot branding is used. The proposed method focuses on the problems of ensuring the uniqueness of animal identification marks. For this, a new mark registration requires a set of comparisons that are carried out by the system using the previously stored set of marks. The uniqueness of the registration mark process is guaranteed



by a similarity metric estimation that considers a set of geometrical invariants features.

2. PROPOSED MARK RECOGNITION SYSTEM

The proposed mark recognition system initially applies an image preprocessing stage for correct image feature extraction. The feature vector is compared to previously stored feature vectors from a dataset using an NN classifier (see Figure-3).

Image preprocessing includes low-level abstraction operations, which aim to improve the image by reducing distortions or highlighting image features useful in the subsequent transformation. In this context, a transformation is performed to grayscale, mainly because there is no relevant color information. The grayscale image is binarized in order to separate the area of interest from the background.



Figure-2. Physical registration act.

Feature extraction

Feature extraction mostly consists in transforming the input data into a set of quantifiable properties called features. In image processing, feature extraction is a form of dimensionality reduction when the image is too large or has redundancy.

Dimensionality reduction by feature selection has several advantages, such as (Hernandez *et al.*, 2016):

- Improving the performance of machine learning algorithms.
- Data understanding, gaining knowledge about the process and helping to visualize it.
- Data reduction, limiting storage requirements and helping in reducing costs.
- Simplicity, possibility of using simpler models and gaining speed.

The set of features is called feature vector and is expected to represent the relevant information of the

object inside the image. A general taxonomy of features that have been employed can be categorized into two groups: general features and domain-specific features (Choras, 2007).

General features are application independent features such as color, texture and shape. These can be further divided into global, local or pixel-level features depending on the relative space used for the calculation. Domain-specific features are application dependent features such as human faces, fingerprints and conceptual features.

For cattle mark recognition, we propose to extract two types of feature vectors: Hu invariant feature vector and Legendre feature vector. Hu and Legendre moment invariants can be classified as shape descriptors. The main idea is to describe objects by a set of measurable quantities that are invariant properties to geometric transformations of images such as rotation, translation and scaling.

Moment invariants

The moment of (p+q)th order in the 2D space is defined as:

$$m_{p,q} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x,y) dx dy \quad (1)$$

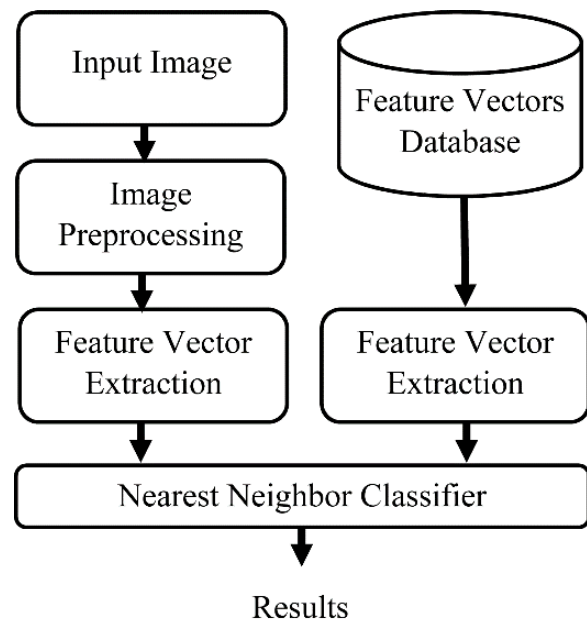


Figure-3. An overview of the proposed recognition algorithm.

Where p and q are nonnegative integers greater than or equal to zero. So, if $f(x,y)$ is a piecewise continuous bounded function, then the moments of all order exist and the moment sequence $\{m_{p,q}\}$ is uniquely determined by $f(x,y)$ and vice versa (Huang and Leng,



2010). However, $m_{p,q}$ may be not invariant when $f(x, y)$ changes by some geometrical operation. Invariant features can be achieved using central moments, such as:

$$\mu_{p,q} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q f(x, y) dx dy \quad (2)$$

where

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad (3)$$

$$\bar{y} = \frac{m_{01}}{m_{00}} \quad (4)$$

Hu invariant moments

Hu moments have been used as basic feature descriptors for images (Hu, 1962). These moments are defined using a central moment definition. For a two-value image I, the $p+q$ central moment is:

$$\mu_{p,q} = \sum_{(x,y) \in I} (x - x_c)^p (y - y_c)^q \quad (5)$$

where (x_c, y_c) is the center of I, and the coordinate (x, y) is a point in I. A set of seven Hu moment invariants with respect to shift, rotation and scaling are defined as:

$$\phi_1 = \mu_{2,0} + \mu_{0,2} \quad (6)$$

$$\phi_2 = (\mu_{2,0} - \mu_{0,2})^2 + 4\mu_{1,1}^2 \quad (7)$$

$$\phi_3 = (\mu_{3,0} - 3\mu_{1,2})^2 + (3\mu_{2,1} - \mu_{0,3})^2 \quad (8)$$

$$\phi_4 = (\mu_{3,0} + \mu_{1,2})^2 + (\mu_{2,1} + \mu_{0,3})^2 \quad (9)$$

$$\phi_5 = (\mu_{3,0} - 3\mu_{1,2})(\mu_{3,0} + \mu_{1,2}) [(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu_{2,1} - \mu_{0,3})^2] + (3\mu_{2,1} - \mu_{0,3})(\mu_{2,1} + \mu_{0,3}) [3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} - \mu_{0,3})^2] \quad (10)$$

$$\phi_6 = (\mu_{2,0} - \mu_{0,2}) [(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} - \mu_{0,3})^2] + 4\mu_{1,1}(\mu_{3,0} + \mu_{1,2})(\mu_{2,1} - \mu_{0,3}) \quad (11)$$

$$\phi_7 = (3\mu_{2,1} - \mu_{0,3})(\mu_{3,0} + \mu_{1,2}) [(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu_{2,1} + \mu_{0,3})^2] - (\mu_{3,0} - 3\mu_{1,2})(\mu_{2,1} + \mu_{0,3}) [3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2] \quad (12)$$

The first six moments are absolute orthogonal invariants of the second and third order. The seventh moment is a skew orthogonal invariant useful in distinguishing mirror images.

Legendre moments

Initially introduced by Teague (Teague, 1980), Legendre moments belong to the class of orthogonal moments, and can be used to attain a near zero value of the redundancy measure in a set of moment functions corresponding to independent characteristics of the image (Teh, 1988). Thus, orthogonal moments can better separate image features based on different modes (Shen, 2000), with translation and scale invariants (Chonga *et al.*, 2004).

For an image I with image intensity function $f(x, y)$ the two-dimensional Legendre moments of order $(p + q)$ are defined as:

$$L_{p,q} = \frac{(2p+1)(2q+1)}{4} \iint_{-1}^1 P_p(x) P_q(y) f(x, y) dx dy \quad (13)$$

where $P_p(x)$ is the Legendre polynomial of order p and is given by:

$$P_p(x) = \sum_{k=0}^p \left\{ (-1)^{\frac{p-k}{2}} \frac{1}{2^p} \frac{(p+k)! x^k}{\left(\frac{p-k}{2}\right)! \left(\frac{p+k}{2}\right)! (k)!} \right\} \quad (14)$$

where $p - k$ must be even. From (Chonga, 2004), the recurrence relation of Legendre polynomials is given by:

$$P_p(x) = \frac{(2p-1) \times P_{p-1}(x) - (p-1)P_{p-2}(x)}{p} \quad (15)$$

So that $P_0(x) = 1$, $P_1(x) = x$ and $p > 1$. From equation (13), the region of definition of Legendre polynomials is the interior of $[-1, 1]$, the image I of $N \times N$ pixels must be scaled so that $-1 < x, y < 1$.

For computational facility, a discrete form of equation (1) is used:

$$L_{p,q} = \lambda_{p,q} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_p(x_i) P_q(y_j) f(x, y) \quad (16)$$

$$\lambda_{p,q} = \frac{(2p+1)(2q+1)}{N^2} \quad (17)$$

where x_i and y_i are the normalized pixel coordinates in the range of $[-1, 1]$, defined as:

$$x_i = \frac{2i}{N-1} - 1 \quad (18)$$

$$y_i = \frac{2j}{N-1} - 1 \quad (19)$$

Finally, we create the feature vector by binding together the different moments:

$$V = \{\phi_i, L_{1,0}, L_{0,1}, L_{2,0}, L_{0,2}, L_{1,1}, L_{3,0}, L_{0,3}\} \quad (20)$$



for $i = 1, \dots, 7$

The numerical values of the moments are very small; therefore, the logarithm of the absolute values is used as a feature. The inter class mean and the standard deviation of the features are used for normalization.

Nearest neighbor classifier

In Machine Learning, the problem of field classification can be stated by extracting knowledge from an input example set $E = \{e_i: i = 1, \dots, n\}$ where each instance is characterized by a set of l property measures or feature vector $V = \{v_i^j: j = 1, \dots, l\}$ and a class label C_i . The objective is to set up a system capable of predicting the class of new examples (Duda *et al.*, 2001), (Galaret *et al.*, 2015). The use of multiple descriptions of images is a way of addressing the problem of improving classification accuracy, so the final capability of a classification process is directly related to the feature vector (Xu, *et al.* 2015).

For computer vision research, the classification process is a fundamental stage in order to deal with some typical problems. In a general way, the state of the art classification methods can be roughly classified into two groups:

- **Learning-based classifiers:** These methods are characterized by a computationally expensive training or learning phase for a set of accurate classification parameters. Examples of these are multilayer perceptron (MLP) (Ravi and Krishna, 2014), radial basis function neural networks (RBFNNs) (Fernandez *et al.* 2012), adaptive neuro-fuzzy inference systems (ANFIS) (Wilk and Wozniak, 2012), support vector machines (SVM) (Cristianini and Shawe, 2010) and k-nearest neighbor classifiers (KNNs) (Bahrololoum *et al.* 2012).
- **Learning-free classifiers:** These methods base their classification decision on the data and are free of a parameter training stage. Statistical techniques belong to this class. The traditional statistical methods of Euclidean minimum distance, quadratic minimum distance, Bayesian decision theory and nearest neighbor classifier are the most popular techniques. The principal weaknesses of statistical methods are their dependence on the correctness of the underlying data assumptions for its success (Mohapatra *et al.* 2015). In contrast, several advantages are attributed to these methods, like handling a huge number of classes, avoiding parameters overfitting and a computational time consuming training stage.

In a Nearest Neighbor classifier, the given test feature vector sample t is compared with each of the stored feature vector v_k on the database using a distance measured $d(t, v_k)$, and the class label that is closest is deemed as the recognition result. The distance

measured $d(t, v_k)$ must satisfy the following properties (Arif *et al.* 2009):

- No negativity: $d(t, v_k) \geq 0$.
- Reflexivity: $d(t, v_k) = 0$, if $t = v_k$.
- Symmetry: $d(t, v_k) = d(v_k, t)$.
- Triangle inequality: $d(a, b) + d(b, c) \geq d(a, c)$.

Let $v_1, v_2, v_3, \dots, v_k$ be the k clusters stored on the database and t the feature vector to classify; the class of t is selected by minimizing the distance $d(t, v_k)$. The vector with minimum difference is the closest matching vector given by:

$$d(t, v_k) = \min_{j=1, \dots, k} \{\|t - v_j\|\} \quad (21)$$

In our system, each new cattle mark insertion or registration requires individual testing in order to ensure the uniqueness of each register. The classification module makes comparison by using a norm through equation (21). Traditionally, the used norm is the Euclidean distance.

3. RESULTS AND DISCUSSIONS

The cattle mark recognition method has been implemented by using the MATLAB R2013b programming environment running on an Intel Core CPU 3.1 GHz with 3.00 GB RAM memory.

We present applications to cattle mark recognition in order to verify the efficiency of the proposed method. The experiments section is divided into three sub-sections. In the first one, we explore the correct classification percentage varying population size in order to observe the behavior of the proposed method when the population size increases. In the second one, we test the accuracy of recognition invariant moments for noisy images by adding Gaussian noise with varying standard deviation. Finally, the time consumed by the three most important phases of the proposed method was measured.

The image set consisted of 100 individual marks: 40 images were obtained from real registers and 60 images were generated by geometric patterns. The images are resized into 253×253 pixels. Figure-4 shows some examples of symbols used to mark cattle. The images in Figure-4a were obtained from real registers and those in Figure-4b were generated by using similar geometric patterns. For real images, some additional preprocessing was applied due to disruptions resulting from paper deterioration caused by environmental conditions and ink scatter. The additional preprocessing includes a global threshold estimation using the MATLAB *graythresh* function, which uses Otsu's method to choose the threshold to minimize the intraclass variance of the black and white pixels. An example of this procedure is shown in Figure-5.

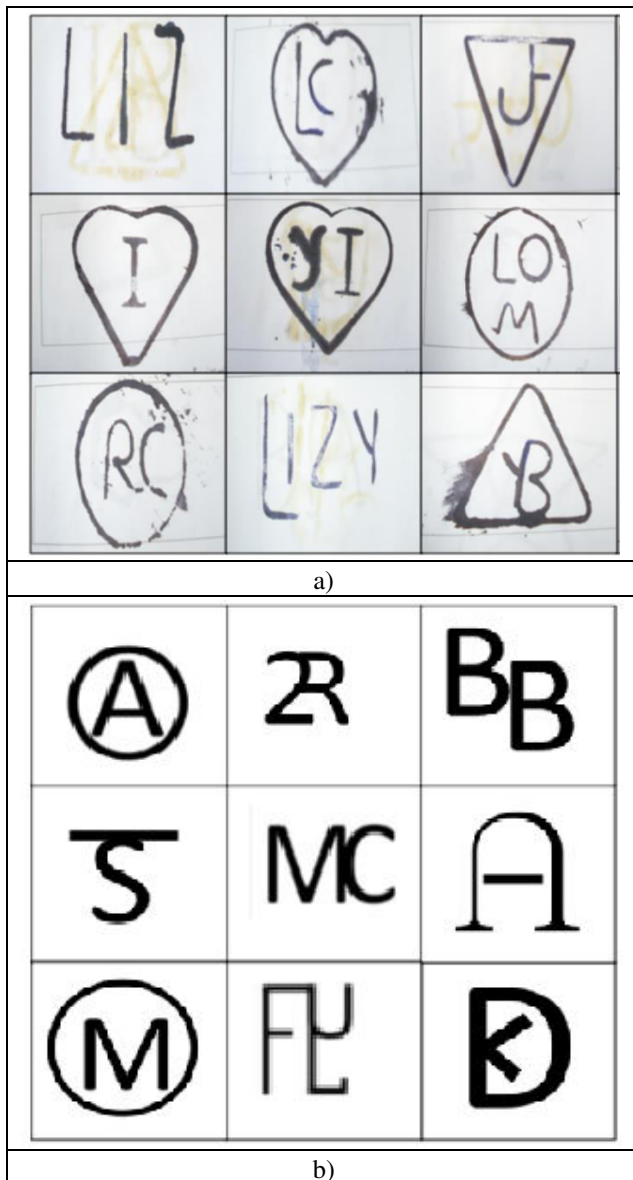


Figure-4. Examples of cattle mark images used for invariance experiments, a) real images and b) synthetically generated images.

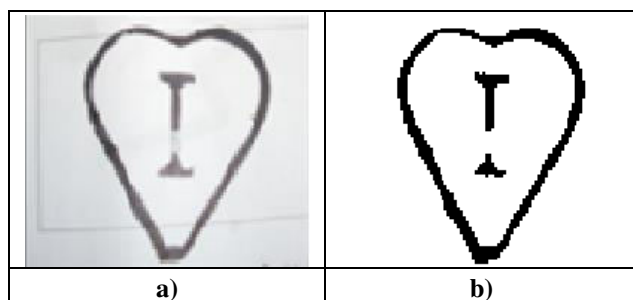


Figure 5. Global thresholding effect on real image binarization, a) real image and b) binarized image.

Experiments varying population size

Due to the similarity of geometrical features of cattle marks, we were interested in analyzing the correct classification percentage of NN classifiers when the size of the population is increased. A different population was set by varying the size parameter generating subsets consisting of 10, 50 and 100 marks. Typically, for subsamples set generation a boosting algorithm is applied, which randomly generates sets. The moments were measured for each one of the selected marks in the set and the percentage of correct classification was averaged. We estimated the accuracy by using HU and Legendre moments separately and combined. Table 1 shows the results.

Table-1. Percentage of correct classification of different population sizes.

| | Percentage of correct classification | | |
|-----|--------------------------------------|----------|-------------|
| | HU | Legendre | HU+Legendre |
| 10 | 97.2 | 98.0 | 99,3 |
| 50 | 95.6 | 96.1 | 98,0 |
| 100 | 94.0 | 95.8 | 97,6 |

Despite the fact that the classification accuracy decreases when the population increases, the average percentage of correct classification using combined HU and Legendre moments has a high rate. This measure is higher than each of the moments separately.

Experiments on noisy symbols

A sub-sample of the image set was used to verify the response of the proposed methods to noise. We selected 20 original images and 20 synthetic images and imposed Gaussian noise with standard deviation varying from 0.1 to 0.4. Examples of these effects are shown on Figure-6. Figure-6(a) shows the original image and Figure 6(b-d) is symbols with noise presence.

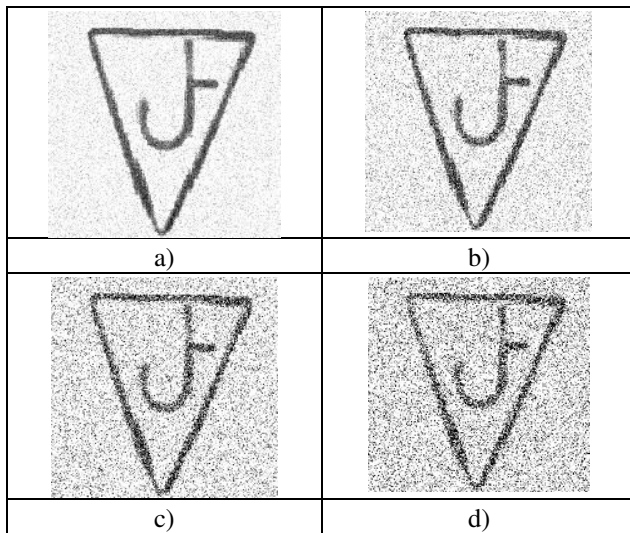


Figure-6. Images with Gaussian noise added from a) SD = 0.1, b) SD = 0.2, c) SD = 0.3 and d) SD = 0.4.

Table-2 shows the average results for noise-free and noise variations for mark classification. This average percentage was measured in 10 image sets. Noise presence affects the classification accuracy; however, the combined moments procedure shows a minor decrease when the noise increases. Even in the presence of noise rate growth, the percentage of correct classification remains at values over 92% and generates higher values than those obtained with moments separately.

Table 2. Percentage of correct classification of noisy images with standard deviation of Gaussian noise varying.

| | Gaussian noise | | | | |
|-------------------|----------------|------|------|------|------|
| Invariant moments | Noise free | 0.1 | 0.2 | 0.3 | 0.4 |
| Hu | 97.0 | 94.2 | 90.3 | 82.4 | 77.3 |
| Legendre | 98.1 | 96.7 | 93.2 | 91.2 | 88.6 |
| Hu+Leg | 99.5 | 98.5 | 97.3 | 95.8 | 92.0 |

Time consumption experiments

The time consumption measure is addressed to determine the computational characteristics of the proposed method in order to include it into online or real time software. We formed different random image sets of size varying from 10 to 100 images. For each group we averaged the time consumption for the three main stages of the proposed method: preprocessing, moment estimation and classification.

Figure-7 shows the time consumption behavior for the three stages. Moment estimation stages required a shorter amount of time. In contrast, the highest computational cost corresponds to the classification

procedure. Despite the fact that the method showed a low computational cost, which makes it possible to be included into real-time processing software allowing local authorities to make cattle mark registration online.

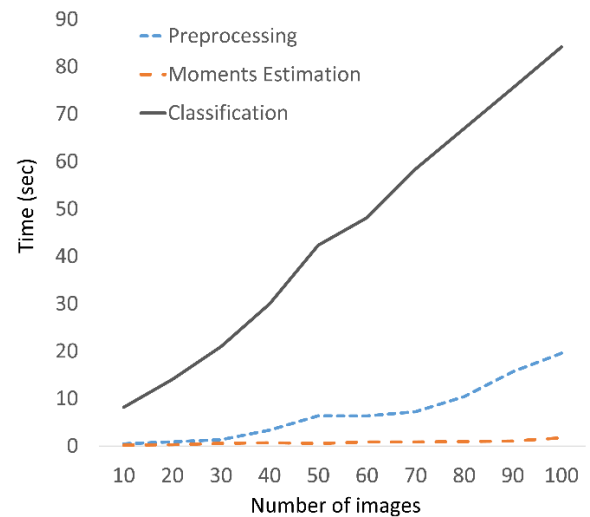


Figure-7. Preprocessing, moment estimation and classification time consumption behavior.

4. CONCLUSIONS

This work introduces a comparative set of experiments of the two most popular moments feature extraction methods, HU and Legendre, to recognize cattle mark images based on an NN classifier. We explored the accuracy behavior of using moments feature separately and combined. The experimental results showed that the percentage of correct classification rates of the NN classifier by using combined moments is higher than the rate of moments separately. However, based on the results, it is possible to assert that including other moment features in order to form a more robust cattle mark signature may have potential advantages for improving recognition.

Computationally, the time consumption measure showed that the method can be used in a real time software system for cattle mark registration processes.

Animal identification based on hot branding does not permit food traceability because it does not allow individual animal traceability. However, hot branding registration permits some control level in those regions with low technical specifications. Therefore, more research addressing the development of a traceability system will permit, in the future, the possibility of having the traceability information centralized, which gives easy and continuous access to information in order to apply programs and policies if needed.



REFERENCES

- Arif T., Shaaban Z., Krekor L. and S. Baba. 2009. Object classification via geometrical, zernike and legendre moments. *Journal of Theoretical and Applied Information Technology*. 7(1):031-037.
- Athilakshmi R. and Wahi A. 2014. Improving object classification using Zernike moment, radial Chebyshev moment based on square transform features: a comparative study. *World applied sciences journal*. 32(7): 1226-1234.
- Badia R., Mishra P. and Ruiz L. 2015. Food traceability: New trends and recent advances. A review. *Food Control*. 57(1): 393-401.
- Bahrololoum A., Nezamabadi-Pour H., Bahrololoum H., Saeed M. 2012. A prototype classifier based on gravitational search algorithm, *Appl. Soft. Comput.* 12(2): 819-825.
- Caja G., Barillet F., Nehring R., Marie C., Ribó O., Ricard E., Lagriffoul G., Conill C., Aurel M.R. y Jacquin M. 1996. Comparison of different devices for electronic identification in dairy sheep. In: Performance recording of animals. Proceedings of 30th biennial session of the international Committee for Animal Recording, EAAP Publication, no. 87, WageningenPers, Wageningen. pp. 349-353.
- Chonga C., Raveendranb P. and Mukundan R. 2004. Translation and scale invariants of Legendre moments, *Pattern Recognition*. 37: 119-129.
- Ryszard S. 2007. Choraś, Image Feature Extraction Techniques and Their Applications for CBIR and Biometrics Systems, *International journal of biology and biomedical engineering*. 1(1): 6-16.
- Cristianini N., Shawe-Taylor J. 2000. An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods, Cambridge University Press.
- Duda R., Hart P. and Stork D. 2001. *Pattern Classification*, second ed., John Wiley.
- Federación Colombiana de Ganaderos - FEDEGAN - FNG. 2006. Plan Estratégico de la Ganadería Colombiana 2019. Colombia: Sanmartín Obregón and Cía., Noviembre de.
- Felmer R., Chávez R., Catrileo A and Rojas C. 2006. Tecnologías actuales y emergentes para la identificación animal y su aplicación en la trazabilidad animal. *Arch. Med. Vet. Valdivia*. 38(3).
- Fernández R. 2002. Trazabilidad alimentaria. Una herramienta decisiva para la seguridad y la protección de los consumidores. *Distribución y Consumo*. 12(62): 5-10.
- Fernández-Navarro F., Hervás-Martínez C., Ruiz R and Riquelme J. 2012. Evolutionary generalized radial basis function neural networks for improving prediction accuracy in gene classification using feature selection, *Appl. Soft. Comput.* 12(6): 1787-1800.
- Galar M., *et al.* 2015. A survey of fingerprint classification Part I: Taxonomies on feature extraction methods and learning models. *Knowledge-Based systems*. 81: 76-97.
- Hernández E., Bolón V., Sánchez N., Álvarez D., Moret V., Alonso A. 2016. A comparison of performance of K-complex classification methods using feature selection, *Information Sciences*. 328(20): 1-14.
- Hu M. 1962. Visual pattern recognition by moment invariants. *IRE Transactions on Information Theory*. 8(2): 179-187.
- Huang Z., Leng J. 2010. Analysis of Hu's moment invariants on image scaling and rotation, *Computer Engineering and Technology*. 7: 476-480.
- Mohapatra P., Chakravarty S., Dash P. 2015. An improved cuckoo search based extreme learning machine for medical data classification. *Swarm and Evolutionary Computation*. 24: 25-49.
- Ravi V. and Krishna M. 2014. A new online data imputation method based on general regression autoassociative neural network, *neurocomputing*. 138: 106-113.
- Ribó O., Korn C., Meloni U., Cropper M., De Winne P. and Cuypers M. 2001. IDEA: a large-scale project on electronic identification of livestock, *Rev. Sci Tech Off intEpiz.* 20: 426-436.
- Shen J., Shen W. and Shen D. 2000. On Geometric and Orthogonal Moments, *International Journal of Pattern Recognition and Artificial Intelligence*. 14(7): 875-894.
- Teague M. 1980. Image analysis via the general theory of moments, *J. Opt. Soc. Am.* 70(8): 920-930.
- The C., Chin R. 1988. On image analysis by the method of moments. *IEEE Trans. Pattern Anal. Mach. Intell.* 10(4): 496-513.



Wilk T., Wozniak M. 2012. Soft computing methods applied to combination of one-class classifiers, *Neurocomputing*. 75(1): 185-193.

Xu Y., Zhang B. and Zhong Z. 2015. Multiple representation and sparse representation for image classification. *Pattern recognition letters*. 68: 9-14, 2015.00) Jun Shen, Wei Shen and Danfei Shen, On Geometric and Orthogonal Moments. *International Journal of Pattern Recognition and Artificial Intelligence*. 14(7) (2000): 875-894.

M. Teague. 1980. Image analysis via the general theory of moments, *J. Opt. Soc. Am.* 70(8): 920-930.

C.H. Teh, R.T. Chin. 1988. On image analysis by the method of moments. *IEEE Trans. Pattern Anal. Mach. Intell.* 10(4): 496-513.

T. Wilk, M. 2012. Wozniak, Soft computing methods applied to combination of one-class classifiers, *Neurocomputing*. 75(1): 185-193.

Y. Xu, B. 2015. Zhang and Z. Zhong. Multiple representation and sparse representation for image classification. *Pattern recognition letters*. 68: 9-14.