ANN ANALYSIS IN A VISION APPROACH FOR POTATO INSPECTION

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ABSTRACT

An image processing methodology for the extraction of potato properties is explained. The objective is to determine their quality evaluating physical properties and using Artificial Neural Networks (ANN's) to find misshapen potatoes. A comparative analysis for three connectionist models (Backpropagation, Perceptron and FuzzyARTMAP), evaluating speed and stability for classifying extracted properties is presented. The methodology for image processing and pattern feature extraction is presented together with some results. These results showed that FuzzyARTMAP outperformed the other models due to its stability and convergence speed with times as low as 1 ms per pattern which demonstrates its suitability for real-time inspection. Several algorithms to determine potato defects such as greening, scab, cracks are proposed which can be affectively used for grading different quality of potatoes.

RESUMEN

Se explica una metodología para extracción de propiedades de papa usando procesamiento de imágenes. El objetivo es determinar su calidad evaluando propiedades físicas y utilizando Redes Neuronales Artificiales (ANN's) se encuentran deformaciones. Se lleva a cabo un análisis comparativo de tres modelos (Backpropagation, Perceptron y Fuzzy ARTMAP), evaluando velocidad y estabilidad para clasificación de propiedades extraídas. La metodología de procesamiento de imágenes y extracción de características se presenta mostrando algunos resultados. Fuzzy ARTMAP superó a los otros modelos debido a su estabilidad y velocidad de convergencia con tiempos tan bajos como 1 ms por patrón, lo cual demuestra lo apropiado del modelo para inspección en tiempo real. Se proponen varios algoritmos para determinar defectos de la papa tales como color verdoso, manchas, grietas y clasificación de forma, que pueden ser empleados de forma efectiva para clasificar diferentes calidades de papas.

Keywords: ANN, ART theory, pattern recognition, Visual inspection

1. INTRODUCTION

Computer Vision is a rapid, economic, consistent and objective inspection technique that has been used increasingly in the last few years. In this work, a methodology is proposed to classify potatoes based on several characteristics obtained from images in real time with a fast digital camera. There are many defects; however, not all of them are common in production lines. In this paper we considered the following group of defects: a) greening, b) cracks, c) scab, and d) shapes. The defects were also classified based on the severity (low, medium and high). In order to process the patterns of shapes extracted from the potatoes, several models of Artificial Neural Networks (ANN's) were assessed first to select the best cognitive architecture for processing the potatoes' information. The stability of the chosen ANN was also evaluated. Section 2 describes the related work. Section 3 addresses the definition of the

ANN's to be evaluated, describing their architecture and main characteristics. Section 4 evaluates each architecture with a common set of patterns in order to determine different parameters such as convergence speed and stability. In section 5, the general methodology for processing the tuber using fast image processing methods and the selected ANN is described and finally, conclusions are provided in Section 6.

The objective of this paper is to propose a new methodology based on the most successful ideas of the state of the art, and proposing a new method using ANN for potato shape classification using fast image processing algorithms able to work in a PC. Our approach complements previous approaches considering the fast learning capability of the selected ANN suitable for real-time inspection processes since we obtained inspection times as low as 1 ms.

2. RELATED WORK

In [1] it is presented a Machine Vision System for Real-Time potato inspection, using a MediaStation 5000 (MS5000) PC compatible board. They use a color camera and get three different images of a single potato with three angles. They classify potatoes by shape, weight, cross-sectional diameter and color. They used a blue color background for separating potatoes from a conveyor belt and their algorithms for separating this are based on the purity of the Hue color (HSI Hue Saturation Intensity). In order to get the greening defect they count, in the green defect area, the number of pixels with certain threshold value.

In [2], a review of the progress of computer vision in agricultural and food industry is presented. The authors made an analysis of several published papers and determine the strong areas and the weaknesses in the agricultural and food grading/inspection. They concluded that the vision systems applied to industry for inspection evaluation purposes provide rapid, economic, hygienic, consistent and objective assessments; however, technology is to be still developed and faster more accurate systems are needed. In [3], an analysis of different techniques and technologies is made. They emphasize the important aspects of the image processing technique coupled with a review of the most recent developments in the food industry.

In [4], a vision system based on 11-SHARC Digital Signal Processors is created to grade potatoes on size, shape, and external defects such as greening, mechanical damages, rhizoctonia, silver scab, common scab, cracks and growth cracks. They used mirrors to obtain a 360° view of the potato with a 3-CCD line-scan camera to inspect the potato in flight as they pass under the camera. The color segmentation procedure uses Linear Discriminant Analysis (LDA) and a Fourier Transform based shape classification technique based on the boundary distances and the centroid of the potato.

In [5], a machine vision system was trained to distinguish between good and greened potatoes and yellow and green apples. They used the HSI (Hue, Saturation, and Intensity) color system for color evaluation and image processing. The vision system achieved over 90% accuracy in inspection of potatoes and apples by representing features with hue histograms and applying multivariate discriminant techniques.

3. ARTIFICIAL NEURAL NETWORKS DEFINITION

The Backpropagation (BP) algorithm is a stochastic steepest descent learning rule used to train single or multiple layer nonlinear networks. The algorithm overcomes some limitations of the Perceptron rule by providing a framework for computing the weights of hidden layer neurons, but also it takes more time for training/testing due to its weight update [6]. The outputs are computed using a sigmoid thresholding of the inner product of the corresponding weight and input vectors. All outputs at stage n are connected to all the inputs at stage n+1. The error is propagated backwards by apportioning them to each unit according to the amount of this error that the unit is responsible for.

The perceptron is a feedforward network with one or more outputs that learn the position of a separating hyperplane in pattern space (a layer for nonlinearly separable pattern pairs). The first layer has fixed weights and the second ones change according to the error in the output. If a neuron shows no error, its weights are not modified. Once the network is trained and if new input becomes available to retrain the network, then it has to be trained with all old patterns and new ones. The training has to be made off-line and the number of epochs could easily reach hundreds or thousands, the same applies to Backpropagation.

Fuzzy ARTMAP [7] is one of the families of the neural network architectures based on ART (Adaptive Resonance Theory) in which supervised learning can be carried out. It allows unsupervised learning as well as supervised learning. This neural network creates several neurons according to the number of patterns and the differences among them. It has several advantages compared with traditional neural networks such as Backpropagation, since it does not suffer catastrophic lose of knowledge and its learning and recognition times are shorter.

The Fuzzy ARTMAP network is based on ART theory and its main working principle is based on the following characteristics, see Figure 1. The ART_a complement coding pre-processor transforms the M**a** vector **a** into the 2M**a** vector A= (a,a^c) at the ART_a field F_0^a. Similarity occurs with the input to F_0^b and there is a mapping field F^{ab} that relates the input pattern with the corresponding output during training stage. Its dynamic characteristics are given mainly by its learning rate (**β**), vigilance parameter (**ρ**) and choice parameter (**α**) in modules A, B and the mapfield.

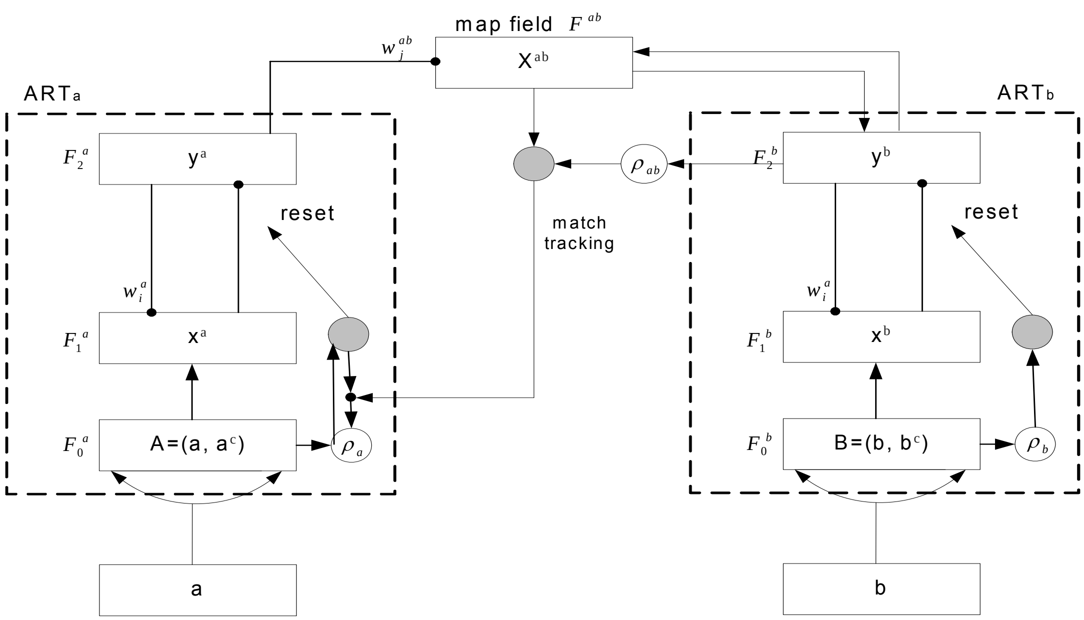


Figure 1. FuzzyARTMAP Architecture

4. ANN EVALUATION

In order to find the best connectionist model for the potato inspection, an evaluation was made. The following subsection shows the experimental results among BP (Backpropagation), P (Perceptron), and FAM (Fuzzy ARTMAP) to select the appropriate model for the vision system. All models were programmed in Visual C++ .NET and assessed using a Pentium D PC @ 2.8 GHz with 512 MB RAM.
Three different shapes were selected as it is shown in Figure 2. A database was formed by a total of 216 patterns (72 for each shape) and it was used for training and testing the ANN's. This database was selected for evaluation because it represents the shape of figures in the form of analogue patterns (they are the Boundary Object Function (BOF) which is explained later).

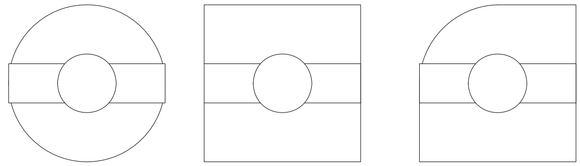


Figure 2. Experimental shapes for ANN's assessment

4.1 Back Propagation

The configuration was as follows: layer_In=185, layer_hidden=200, layer out=4, weights for layer 1,2: Random weight [-2.0,2.0], layer 3, Random weight [-1.0,1.0]. The learning rate was α=0.7 and the maximum allowed error was 0.12. Other experiments were made using topology 185-300-4, learn rate α= 0.85, 185-250-4; however, they showed to be slower.

Five experiments were carried out and considering that this ANN depends on weights selected randomly, the experimental results were averaged. Figure 3, shows the performance of the ANN during learning. There were 3 objects to recognize and the classification started with a 64.16% error due to the random weight selection. The error means the percentage of patterns that are not recognized from the universe of 216, from 0% to 100%. In five experiments, the best case showed 675 epochs to reach 0% error in 57.593 s (training). The worst case showed 1332 epochs recording a final time of 116.375 s.
This model showed a relatively fast reduction of error the first 130 epochs (see fig 3), however, to achieve 100% recognition, it took many epochs more as compared with the other connectionist models.

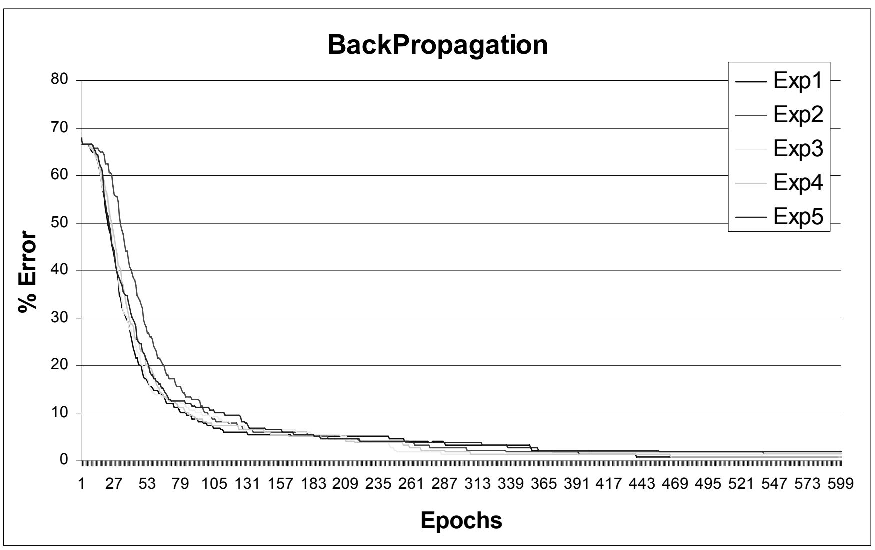


Figure 3. a) Backpropagation Performance (only 600 epochs are shown)

4.2 Perceptron

The Perceptron architecture was considered for evaluation because it can always reach a no-linear patterns classification properly with enough number of neurons in layer 1 (it means the separation layer). In [8], it was demonstrated that one hidden layer is sufficient for performing any arbitrary transformation using enough nodes. This means that it can correctly classify any input vector using enough number of neurons (and also enough number of training epochs). This model was considered for comparison also because of its high speed in training/testing compared with BP. Five experiments were made. The initial weights were randomly selected and the results varied accordingly. The used configuration included 185 Inputs, 4 Outputs, 450 neurons in Layer1(10 C/N=Connections per neuron), Random weights [-2.0, 2.0], 4 neurons in Layer2: (**185** – **450** 10C/N – **4**), Threshold: 0.0 (both layers, signum threshold device), **α**= 0.85. Other experiments were made using **185** – **450** (6, 8, 10, 12 C/N) – **4**, **185** – **350** (6, 8, 10, 12 C/N) – **4**, **α**=0.75, showing very similar results. The network behaviour starts with an average error of 63.8% (see figure 4). This ANN showed a much better performance compared to BP. In the best case it reached 0% error in 41 epochs and a training time of 0.8112 s. In the worst case it took 83 epochs corresponding to 1.734 s in training.

Many researchers prefer to use BP because P always uses fixed weights in the separation layer and also random fixed connections. Those weight values do not adapt to the system, then, it is likely to have non optimum values for the first selection. However, the network always achieves the correct classification.

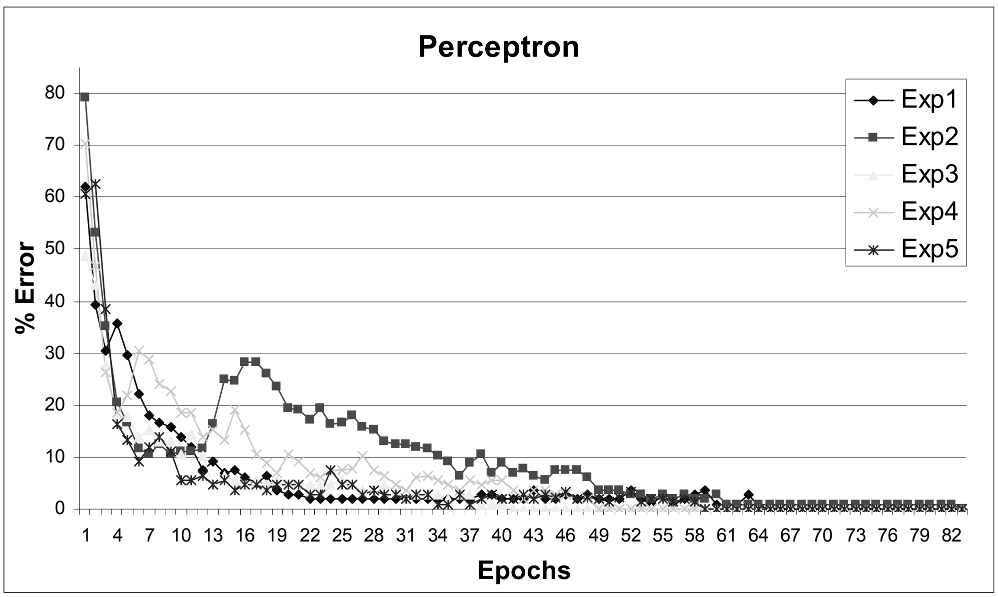


Figure 4. Results of Perceptron.

4.3 Fuzzy ARTMAP (FAM)

The configuration for this architecture was limited to 2 epochs and its configuration employed $\boldsymbol{\rho_{ab}}$ =0.8; **β**= 1.0**;** $\boldsymbol{\rho_a}$ = 0.7; $\boldsymbol{\rho_b}$ = 1.0; **aF1Size**= 185; **bF1Size**=4. For all experiments **α** was set to 0.1 (choice parameter). Five experiments were carried out. This ANN does not depend on random values and the results were obtained in epochs/%error metric parameter.

This ANN starts from an error of 100% (knowledge, i.e. neurons are generated at the beginning while learning). The network reached a fast 0% error in one epoch. The best training time was 0.172 s and the worst 0.188 s. For all cases, the generated Knowledge Base (internal knowledge representation of the network) showed the same behaviour: this model generates as many neurons as necessary in order to classify a pattern and the number of neurons depends on the differences among patterns of the same group and it also depends on the $\boldsymbol{\rho_a}$,$\boldsymbol{\rho_b}$ parameters.

4.4 ANN Comparison

Table 1 shows the experimental results for the shape pattern classification using the 216 patterns (test and train). The time is given in seconds.

ANN \ time (s)	Exp1 Train	Exp1 Test	Exp2 Train	Exp2 Test	Exp3 Train	Exp3 Test	Exp4 Train	Exp4 Test	Exp5 Train	Exp5 Test	Average Train	Average Test
BACKPROPAGATION	79.625	0.047	116.375	0.047	68.734	0.047	57.593	0.047	74.657	0.047	79.3968	0.047
PERCEPTRON	1.391	0.031	1.734	0.031	0.8112	0.016	1.109	0.047	1.203	0.047	1.24964	0.0344
FUZZY ARTMAP	0.188	0.015	0.187	0.015	0.187	0.016	0.172	0.016	0.172	0.016	0.1812	0.0156

Table 1. Results of the ANN experiments.

We can see from Table 1 that the best neural network was FAM with a training time in the order of milliseconds. The worst case was with BP taking approximately 80s for training.

An advantage of FAM, in comparison with the other two models, is that it does not need to train all patterns again each time a new one is added, and it can be trained on-line. BackPropagation showed a Train/Test time of 367.577ms/0.217ms per pattern, the Perceptron, 5.78ms/0.159 ms per pattern, and Fuzzy ARTMAP 0.838 ms/0.0722 ms per pattern. The training and testing time for all patterns is shown in Figure 5.

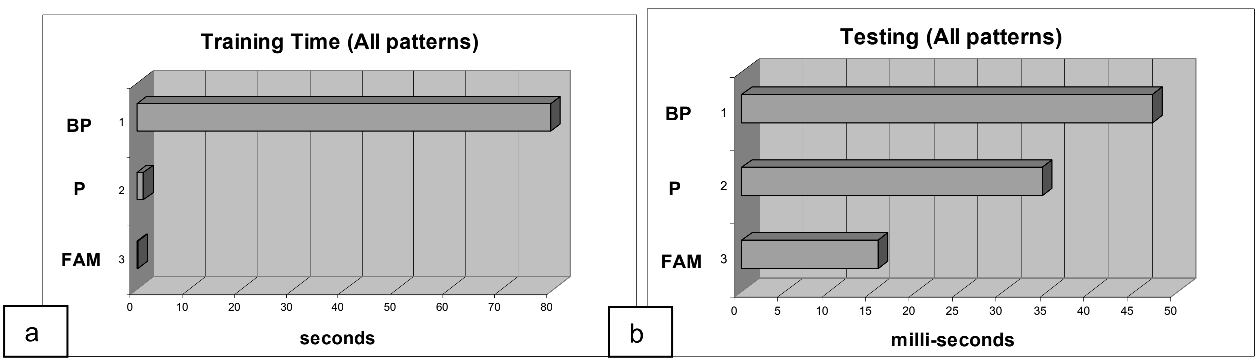


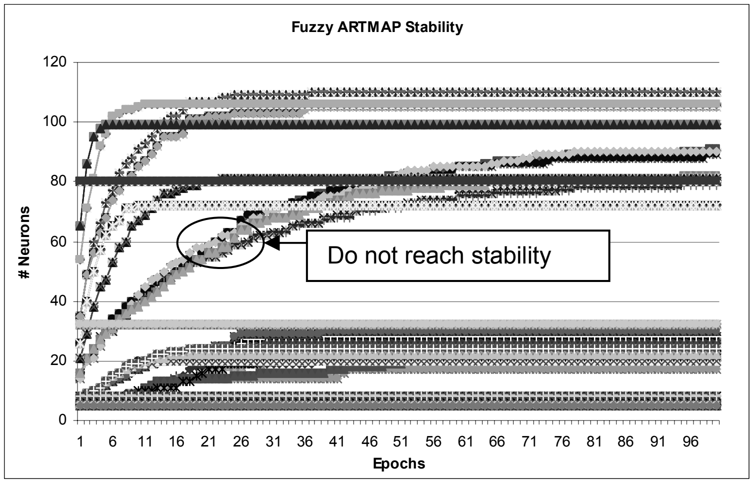
Figure 5. ANN's Training/Testing average time

The FAM was selected because of its incremental knowledge capabilities but mostly because of the fast recognition and geometrical classification responses. The next subsection shows an analysis of the FAM stability-sensibility parameters in order to select the best configuration for the vision system.

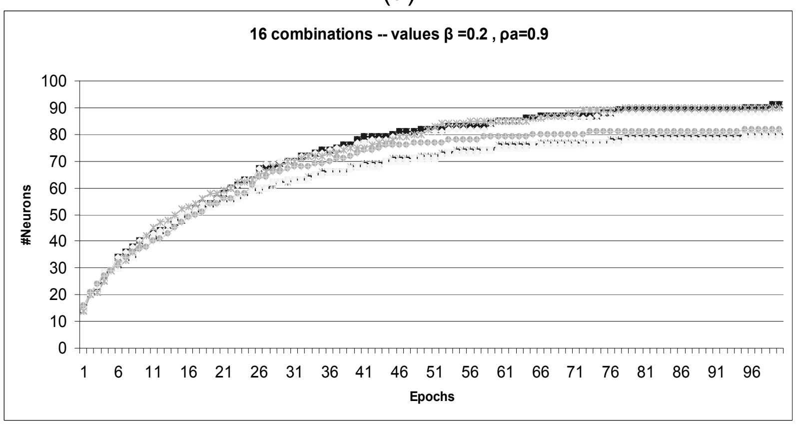
4.5 FAM Sensibility-Stability

For selecting the best parameters, a simulation varying $\boldsymbol{\beta}$, $\boldsymbol{\rho_a}$, $\boldsymbol{\alpha}$ and $\boldsymbol{\rho_{ab}}$ was made. For information about these parameters the reader is referred to [7]. A group of values was combined obtaining 256 different behaviours (4^4). 10 simulations were made using 1, 2, 5, 10, 15, 20, 30, 50, 70 and 100 epochs with a total of 2,560 different training/testing runs for all patterns.

Figure 6a is a 100 epochs experiment with the evaluation patterns. This experiment was carried out for testing the stability of the network and for choosing the best parameters for the proposed methodology. The graphic shows that the combinations of the parameters in the middle part of the graph do not reach stability and the network continues creating neurons. The pattern recognition level does not improve in some cases (the network stability is reached when no more neurons are created). Results indicated that $\boldsymbol{\beta}$ and $\boldsymbol{\rho_a}$ determined the stability and the convergence to %0 error. The other combination for the four parameters (without the network responses in the middle) always reached stability but in some cases they never reached the 100% correct classification. In Figure 6b, using $\boldsymbol{\beta}$ = 0.2 and $\boldsymbol{\rho_a}$ = 0.9 and 16 combinations (varying the other 2 parameters 4 times), when $\boldsymbol{\rho_{ab}}$ was equal to 0.9 and 0.95, the network was able to classify all patterns correctly; however, it was unstable because it continued creating neurons due to the low value of $\boldsymbol{\beta}$.



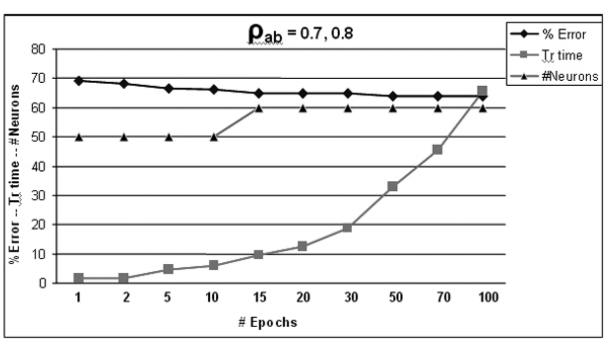
(a)



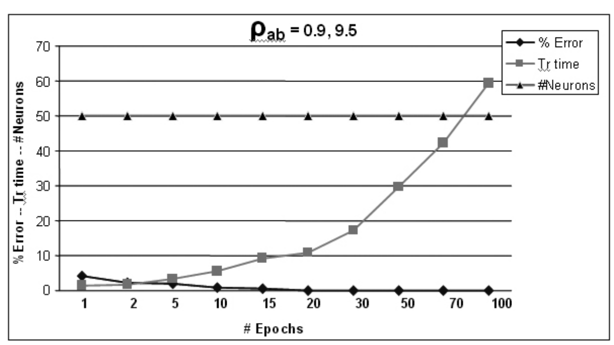
(b)

Figure 6. a) Sensibility-Stability of FAM for 100 epochs, b) Stability with $\boldsymbol{\beta} =$ *0.2,* $\boldsymbol{\rho_a}$ *= 0.9*

The figure 7a shows % Error, Training time, and # Neurons for different epochs. Training time is given in milliseconds and must be multiplied by 10 while # Neurons must be divided by 10. The error never reached 0% when $\boldsymbol{\rho_{ab}}$ <0.9.



(a)



(b)

*Figure 7. Tr Time*10, and #Neurons/10. Parameters* $\boldsymbol{\beta}$*=0.2,* $\boldsymbol{\rho_a}$*= 0.7,* $\boldsymbol{\alpha}$*=0.1. a)* $\boldsymbol{\rho_{ab}}$ *= 0.7, 0.8. b)* $\boldsymbol{\rho_{ab}}$ *= 0.9, 0.95 (both cases showed same behaviour).*

In Figure 7b, the 0% error is reached in 15 epochs, with the same **β =**0.2 and **ρ_a**=0.9. When **β>= 0.5** the classification was always successful. The value of **ρ_a** defines the number of neurons per group that the ANN can generate; however, the higher **ρ_a**, the longer the time it takes to train and test. When **β=1.0**, the learning is reached in only one epoch with 0% error. **ρ_a** can be set according to noise level tolerance. The parameter **α** (choice parameter) showed no high influence in the training/testing. Having **ρ_{ab} >0.9,** was a key value to classify properly when **β** < 0.5. Once the analysis was completed, the methodology was proposed and the ANN selected.

5. GENERAL METHODOLOGY

5.1 Object segmentation.

A firewire (IEEE 1394) Basler f602c camera was used to obtain the potato images. The images were obtained on-line with a camera resolution of 640x480 pixels and a full speed of 100 fps [9]. The camera setup employed structured light during segmentation. In the pre-processing stage, we used an erosion-dilation morphological operator with a disk of 9x9 when multiple potatoes were found in the scene. Some experiments were carried out only with erosion using different disk shapes (5x5, 7x7) square and the combination of erosion-dilation with different shapes and values. It was found to be appropriate to use a 9x9 disk. Other implementations were considered [1, 2, 4] using only one potato per image and 3 potato images separated 120º separation (among them) as an alternative of implementation.

5.2 Extraction of Properties

Further pre-processing for image quality was made by applying basic filters. A maximum filter (window 3x3) was used first and then an average filter (window 3x3) to reduce any possible noise particles. Those filters were determined through experiments. After that, a threshold value is applied to binarize. This threshold was calculated by using the medium value from the intensity data histogram (middle part of background and object).

The perimeter calculation for every piece in the master image was performed after the binarization and segmentation. The search is always accomplished from left to right and from top to bottom. Once a white pixel is found, all the perimeter is calculated with a search function based on a modified 8-connectivity chain code that generated coordinate values instead of chain code. This technique will surround any irregular shape, and will not process useless pixels of the master image, which makes the algorithm suitable for real time processing. The proposed procedure for centroid calculation is performed at the same time that the coordinates of the perimeter are calculated without using the *NxM* pixels box, (*Bounding Box*, where N= rows, and M=columns).

The coordinates of the centroid (*Xc, Yc*) are calculated with the following procedure:

> ***(1)*** *If a new perimeter pixel is found, the value of i, j coordinates from pixel to left and to right are added, until a border pixel is found.*
> ***(2)*** *Mark the current perimeter pixel as visited*
> ***(3)*** *While a new perimeter pixel is found, repeat step 1-2.*

Equation (1) is used for centroid calculation in binarized images:

$$X_c = \frac{\sum_{x,y} j}{A}, Y_c = \frac{\sum_{x,y} i}{A} \qquad (1)$$

Where A is the area or number of pixels of the piece (found while calculating perimeter).

For calculating the angle of the potato, the coordinates of the largest line is used. The equation for the distance between two points was used to corroborate if it was the largest straight line, and also if it passes trough the centroid (2) with an error margin of 5%.

$$Y_C - y_1 = m(X_C - x_1) \quad (2)$$

Slope is obtained using (3):

$$m = \frac{y_2 - y_2}{x_2 - x_1} \quad (3)$$

Figure 8 shows some of the properties to be found.

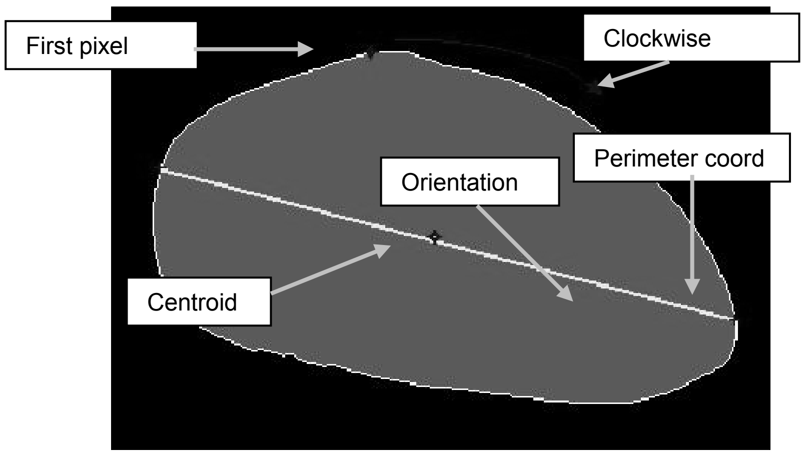


Figure 8. First properties calculation of the potato

For the shape classification, a Boundary Object Function (BOF) is generated. It is the function that describes a specific object border and it will vary according to the shape. The centroid, the coordinates of the perimeter and the distance from the centroid to the perimeter points are used to calculate the BOF. With the coordinates P_1 (X_1, Y_1) and P_2 (X_2, Y_2), equation (4) is applied to determine the longest straight line that fits inside the potato shape:

$$d(P_1, P_2) = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2} \quad (4)$$

5.3 Defects finding

The greening defect is detected using the HSI format (Hue, Saturation, and Intensity). The Hue describes the purity of the colour in a range of 0º to 360º. This format is calculated using the base of RGB (Red, Green, and Blue) for each pixel on the original image. Considering that green is a primary colour, this defect is found using the range between 90º and 135º approximately (HSI). Once the potato image is binarized, all properties have been found and its shape has been classified, then the cracks are determined.

Segmentation inside the tuber is done using the same pre-processing with filters (window 3x3) and a threshold is applied for each defect. When this processing is done, ia binary image for each different defect is obtained and it is classified according to its geometrical characteristics. Figure 9 shows the detection of cracks and scabs. To find a crack, different threshold values were used as well as color, area and the relation large/width.

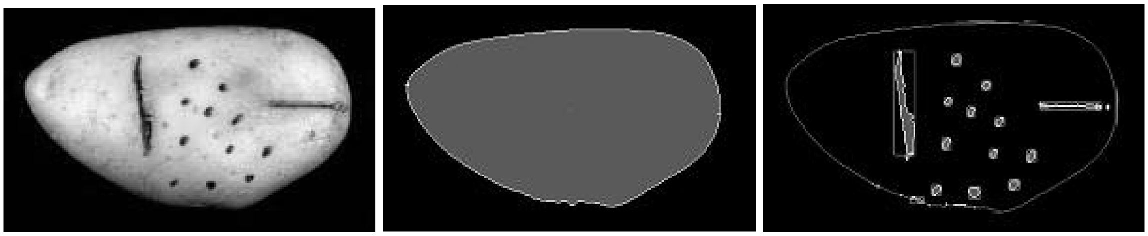


Figure 9. Cracks and scab detection

The algorithm classifies two cracks on the potato and the rest as scab. If it is necessary to find another colour defect, we can apply the proper segmentation and obtain the small particles related to that object after a binarization and to carry out proper measurements.

5.4 Objects Classification

In order to classify the shapes, the BOF (Boundary Object Function) is used, which is defined as the vector of distances from the centroid to the perimeter coordinates. See Figure 10. By grouping different shapes, it is possible to detect defects as misshapen or second grow. The proposed method uses only 2 images per potato for training the neural network, instead of using multiple patterns. This strategy makes the training very easy and it is only necessary to generate the classification groups and to label them according to their properties and defects relation. The detection time was shorter than 1 millisecond. The overall success rate in classification was 93.8%, using 20 different complex objects in a total of 480 patterns (24 each object), rotated for different positions and also the mirror of it.

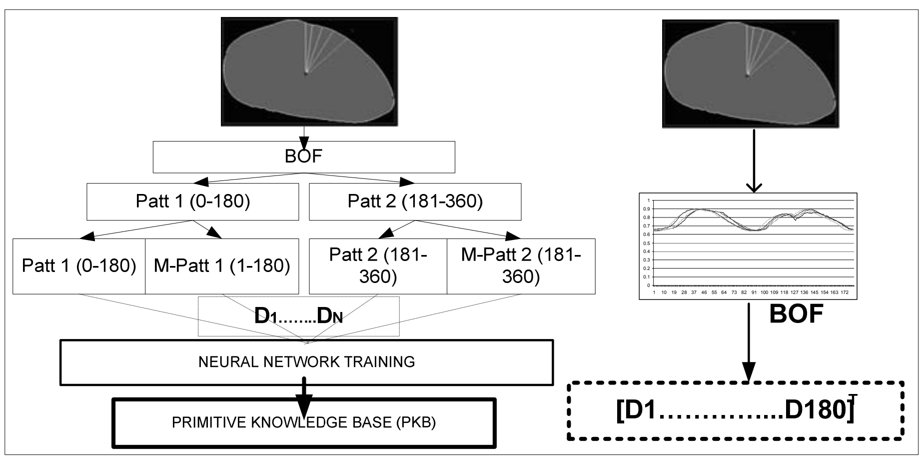


Figure 10. Left, PKB Base generation using two simple patterns. Mirrors are generated to increase prediction success. Right, Descriptor vector generation

5.5 Grading classes

As proposed in [4], the considerations for grading the potatoes in quality classes using the severity of the defects are summarised in Table 2 along with some other considerations.

Defect	Good	Light	Medium	Severe
Scab	(1-2 spots) < 3%	(2-4 spots) < 6.5%	(5-15 spots) < 15%	(14-40 spots) < 25%
Greening	0-1%	1-2%	2-5%	>5%
Cracks	Small cracks	1/5 length of the tuber are not allowed		
Shape	Group shapes 1	Group shapes 2	Group shapes 3	Group shapes 4

Table 2. Grading classes in percentages of total potato area

All percentages are calculated in relation with the total potato area from the image. The pixels are counted. In the case of potato shape, it is suggested to have four shape groups as the output of the ANN and the BOF as the input of the network.

6. CONCLUSIONS

A performance analysis for different connectionist models using the same data base was carried out. The results showed that FuzzyARTMAP (FAM) outperformed Backpropagation (BP) and the Perceptron (P) in terms of stability and convergence time using a geometrical data base. During experiments, FAM showed very short times for training and testing with values lower than 1 ms per pattern. Considering this fast learning capability, the FAM was selected for inspecting the shape of potatoes.

The properties extraction for defects detections was achieved using segmentation of colour and grey-scale images applying different algorithms. An evaluation was made in order to find defects and suitable experiments were carried out to asses the algorithms accuracy. 25 potatoes were used with different defects.

The developed methodology consisted in determining misshapen potatoes as well as, additionally, the number of scabs, level of greening, crack size and shaping, which are all important features to look at when working with potatoes in production lines.

Due to the fast processing algorithm, the methodology is suitable for quality control in production lines; further work is envisaged using certified potatoes for calibrating the threshold values for industrial application, and to use the neural architecture for finding other important defects such as excessive sugar content, which is a current problem within the potato chip industry that requires the use of thermal imaging.

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Obtained a BEng from the Autonomous University of Queretaro in 2004. He obtained a MSc in Mechatronics at Aachen University of Applied Sciences, Germany in 2007 and, currently, he is a Research Assistant at the Robotics and Advanced Manufacturing Systems Research Group at CINVESTAV-Saltillo. He has published over 30 papers in refereed international journals and proceedings in several areas of computer science. He is a member of the Mexican Society of Robotics (AmROB), and of the IEEE.

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Obtained a BEng from The National Autonomous University of Mexico (UNAM) in 1991. He also worked as Research Assistant and lecturer at the same university from 1991 to 1994. He obtained a MSc in Instrumentation at UMIST, U.K. in 1996 and a PhD in Intelligent Robotics at The Nottingham Trent University, U.K. in 2000. He was the founder and leader of the Mechatronics and Intelligent Manufacturing Systems Research Group at CIATEQ, A.C. from 2000 to 2006 and, currently, he is a Principal Researcher at the Robotics and Advanced Manufacturing Systems Research Group at CINVESTAV-Saltillo. Dr. Lopez-Juarez has published over seventy papers in refereed international journals and proceedings in the area of Instrumentation, Self-adaptive Industrial Robots and Neural Networks and has also served as reviewer for International Conferences and Journals. He is a founder member of the Mexican Society on Mechatronics (AMM), member of the Mexican Society of Robotics (AmROB), member of the Mexican Society for Computer Science (SMCC), member of the IEEE-Robotics and Automation Society and also member of the IEEE-Computational Intelligence Society.

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Hsieh received the Ph.D. degree in industrial engineering from Texas Tech University, Lubbock, in 1995. He is an Assistant Professor and a member of the Graduate Faculty of Texas A&M University, College Station. He holds a joint appointment with the Department of Engineering Technology and Industrial Distribution and the Department of Mechanical Engineering at Texas A&M University. Dr. Hsieh received a National Science Foundation CAREER Award in 2003. He has also served as a Summer Research Fellow for the U.S. Air Force (1998, 2003) and U.S. Army (1999–2002), for which he conducted research on thermography and vision system design and characterization. His research interests include manufacturing automation and system integration, intelligent manufacturing system design, thermal signatures for process and product characterization, and simulation and modeling. He is also the Director of the Rockwell Automation Laboratory at Texas A&M University.