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Use of artificial vision techniques for diagnostic of nitrogen nutritional status in maize plants

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ABSTRACT

The identification of the nutritional status of maize by foliar chemical analysis requires sampling of leaves when the plant is in an advanced stage of development, hindering corrective action in ongoing cultivation, if deficiency detection of a specific nutrient occurs. An artificial vision system (AVS) is a set of methods used for analysis and interpretation of images. Therefore, an AVS is being developed to identify nutrient deficiencies at different stages of plant development, especially in the early stages of growth, which may contribute to early diagnosis and correction in the same cycle of growth. The objective was to evaluate methods of digital image processing to develop the AVS to diagnose induced nitrogen deficiency in maize leaves. The experiment was done in greenhouse and the treatments were N doses (0.0; 3.0; 6.0 e 15.0 mMol L^{-1}) combined with three growing stages (V4, V7 and R1). The images of maize leaves were digitized in 1200 dpi. After scanning, leaves were chemically analyzed for N content and was determined the dry mass of plants. The studied methods in AVS were: Volumetric Fractal Dimension (VFD), Gabor Wavelet (GW) and VFD with canonical analysis. The omission and reduction of nitrogen in maize plants resulted in typical symptoms of N deficiency. The AVS was able to identify levels of nitrogen deficiency in the early stages of development of corn, with global percentage of right of 82.5% at V4 and 87.5% at V7. The GW technique with color images resulted in the better method for features extraction.

1. Introduction

The improvement of methods for identification of the nutritional status of plants, combined with the need for improvements in the efficient use of nutrients present in soil or applied through fertilization to obtaining high yields by crops, have led to search for new technologies, of the viewpoints agronomic, economic, environmental or operational. Mineral nutrients have essential role in plant metabolism in such a way that in cases where one of the nutrients is not in adequate amount the whole metabolism is prejudiced. Such disturbs usually can be identified by symptoms in plant development, such as chlorosis and necrosis, reduced growth and similar anomalies (Malavolta, 2006).

The Nitrogen (N) deficiency symptoms begin as leaf chlorosis, from tip to base as an inverted "V" pattern; dryness from the tip of the old leaves towards the central nervure; necrosis followed by leaf tearing, and thinning of stalks (Taiz and Zeiger, 2006; Marschner, 2012). Nitrogen is a constituent of all amino acids, amides, proteins, nucleic acids, nucleotides, polyamides and cytochromes, and is part of chlorophyll molecule (Malavolta, 2006). Lack of N delay cell division at the growing gems, decreasing leaf area and plant size, with prejudice of grain yield (Coelho, 2007).

The evaluation of nutritional state of the plants is usually done through chemical analysis or visual evaluation. Leaf chemical analysis imply sampling at certain phenological stage, which in practice does not allow to take remediation actions for the crop being cultivated. Visual diagnose is subjected to errors in interpretation because visual symptoms can occur simultaneously and also be confounded with pest attack or disease. Therefore, visual diagnose depends strongly on the operator's experience. The use of biometric measurements of leaves, related to the shape, area, texture and ribs, among others, provide quantitative, objective and accurate information that can be employed in the study of plant nutrition.

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In this context, computational models of artificial vision and mathematical models can contribute to a more detailed analysis of foliar structures through benchmark techniques and information extraction (Backes and Bruno, 2008).

An artificial vision system or computational vision may be defined as a set of methods and techniques through computer systems, which are able to interpret an image automatically or semi-automatically (Punam and Udupa, 2001). And are constituted in the steps: acquisition, image segmentation, feature extraction and classification/identification (Bruno, 2000; Gonzales and Woods, 1993). In literature there are several methods of taxonomies for image segmentation. However, the most traditional is adopted by Gonzales and Woods (1993), which defines three categories of segmentation: thresholding, based segmentation on edges and based on regions. Other methods are based on colors (Lim and Lee, 1990; Gonzalez et al., 1990; Moreira, 1999), the ones using neural networks and fuzzy logic (Bezdek et al., 1999) and those based on genetic algorithms (Ankenbrandt et al., 1990). Chromatic analysis is considered the information concerning the color. Among the methods used in this category of segmentation, can highlight the analysis of chromatic histograms (Cheng et al., 2001), chromatic moments (Stricker and Orengo, 1995) and set of colors on mappings (Cheng et al., 2001). The segmentation process selects regions for images analysis. The feature extraction step consists of methods to assess the regions of the images for their characterization. This step, the texture analysis considers the distribution and organization of pixels in a certain image region. In this context, methods that use measures like fractal dimension and lacunarity can measure the complexity of images, and generate digital signatures to characterize the image (Backes and Bruno, 2008).

The application and use of image analysis is utilized in agriculture for some time now, mostly in precision agriculture. Yang et al. (2000) applied artificial neural networks (ANN), trained with the back-propagation algorithm, to the development of a model capable of distinguishing young maize plants of weeds plants. Burks et al. (2005) used the same algorithm to study the recognition of weeds plants. Baesso et al. (2007) assessed the use of spectral indices, taken from digital images, to discriminate different doses of nitrogen in common bean. Sena Júnior et al. (2008) identified through image analysis nutritional stages of wheat plants. Silva et al. (2014) evaluated different methods for feature extraction in images of maize leaves in the V4 stage, grown in greenhouse under nutritional deficiency induced of magnesium. With the obtained results, it was found global percentage of right 76% with reliable Kappa index. Silva Júnior et al. (2012) determined the percentage of vegetation cover of weeds plants in the crop beans, under the no-tillage and conventional, using digital image processing and geostatistics. Abrahão et al. (2013) conducted a study of classifiers based on different combinations of bands and spectral indices of original images to discriminate foliar nitrogen and chlorophyll, also in the crop beans.

Being so, the use of image processing in agriculture can be an auxiliary important tool in the soil and plant management. The present research was focused in the development of an AVS for N diagnosis in maize plants, for further validation in field. The objective of this study is to present an evaluation of methods of image processing used to identify and evaluate induced N deficiency in maize.

2. Material and methods

2.1. Experiment in greenhouse

The experiment was done in a greenhouse of the Animal Science Department of the College of Animal Science and Engineering Food (FZEA/USP) at the Pirassununga-SP campus. The crop tested was maize (*Zea mays* L.), hybrid DKB 390®, grown in a hydroponic system in nutrient solution.

Experimental design was fully random, in a 4×3 factorial with four replications. The factors established for the study consisted of four levels of N concentration in nutrient solution: T1 = complete omission ($0\ \mathrm{mMol\ L^{-1}}$), T2 = 20% of full level ($3.0\ \mathrm{mMol\ L^{-1}}$), T3 = 40% of full level ($6.0\ \mathrm{mMol\ L^{-1}}$) and T4 = full level ($15\ \mathrm{mMol\ L^{-1}}$), combined in three time sampling of collecting leaves (phenological stage), when plants were with four fully expanded leaves (V4), seven leaves (V7) and silking (R1), totaling 48 experimental units (4 level of N $\times$ 3 sampling stage $\times$ 4 replications). The concentration of elements in nutritional solutions was determined after a previous trial having the Hoagland and Arnon (1950) solution as reference.

Seeding was done in plastic trays filled with washed sand until two weeks after emergence. After that, two plants were transferred to 3.5 L pots (experimental units) and supported by a piece of foam and maintained there until stage V7, when they were transferred to 10 L pots until stage R1. After transplanting, plants were kept in a 50% diluted nutrient solution for them to adapt, during 5 days. Nutrient solutions were replaced 15 days after transplanting, and henceforward weekly. When needed, pot solution was leveled with deionized water and pH adjusted between 5.0 and 6.0 with HCl 1 N and NaOH 1 N. Each pot had air bobbling during 10 s at each 30 s interval.

In each collecting times established, 16 pots (experimental units) were sampled (sample destructive). Sampled material was split in (a) above ground portion (shoot, Sh); (b) root (Rh); (c) index leaf (IL) of the growing stage (V4 = leaf 4; V7 = leaf 7, and R1 = opposite leaf below the first ear) and (d) old leaf (OL). At all sampling times (V4, V7 and R1), the OL collected in the corn plant corresponded to older leaf that was not senescent.

The shoots, index leaves and old leaves after collection of images, were rinsed in deionized water. The roots were washed in running water and then were washed in the following order: water with a neutral detergent, deionized water, hydrochloric acid (HCl) diluted in deionized water and finally deionized water. Posteriorly, the plant parts were dried in an oven with forced air circulation at a temperature of 65 °C, for approximately 72 h, to determine the dry mass and then grind with 2 mm screen and saved in plastic bags for further analyses of N determination according to methodology described in Bataglia et al. (1983).

2.2. Statistical analysis for dry mass and N concentration

Statistical analysis model below was accomplished for the dry mass yield and accumulation of nitrogen in shoot and root of maize plants, and N concentration in index leaves. Results were statistically processed using variance analysis. According to Steel et al. (1997) the statistical model used was as follows

$$\mathrm{Yijk} = m + \mathrm{Ei} + \mathrm{Nj} + \mathrm{ENij} + \mathrm{eijk} \tag{1}$$

In the model, Yijk is the observed value at parcel that received ij treatment on repetition k; *m* is the average; Ei is the effect of the development stage of maize; Nj is the effect of nitrogen levels at parcel; eijk is the effect of uncontrolled factors at parcel that received ij on repetition k. When the *F* test was significant ($P \leqslant 0.05$) only for Nj, has been done only one polynomial regression analysis for all stages. When the *F* test was significant ($P \leqslant 0.05$) for ENij, in the other words, when there was interaction between the levels of N applied and the developmental stages, the splitting aimed to study the levels within of the Ei for the N content in the index leaves. And for the accumulated N in different plant parts were studied developmental stages within each level of N (Nj) in the nutrient solution.

2.3. Artificial visual system

In Fig. 1 presents a diagram of the proposed system, with steps steps of images analysis according Gonzales and Woods (1993). The proposed system consists in four main parts: early processing, texture sample generator, texture feature extraction and pattern recognition. Several leaves are scanned by the same time using a scanner, providing a digital image. In the first step of the system, the early processing part consists in algorithms to remove the background and after that, the foreground leaves have to be split and oriented horizontally. For each leave, a texture window is taken. In this task, a large number of small windows are extracted from the leave image. For each leave, a texture window is taken. In this task, a large number of small windows are extracted from the leave image. The samples pass by statistical analysis and if they are not representative taking into account the whole leave, it is disregarded. To check the samples are representative, it is compared as a mean of all windows obtained from the leave. These tasks (windows extractions and selection) are performed automatically by the "Texture sample generator module". On the "texture feature extraction" module, texture analysis methods are applied into each window and the feature vector is created by each one. On the last part of the system, the feature vectors can be used for training the model or to yield a report, checking in which class it belongs. It is done using a supervised classification model based on the naive Bayes method.

Leaves were scanned in a regular desktop scanner (HP Scanjet 3800) at 1200 dpi resolution and saved in tiff format. In each sampling event (according to plant stage), IL and OL of 16 pots were collected (4 treatments and 4 replications). Since two plants were cultivated in each experimental unit, 8 IL and 8 OL were obtained for each treatment.

In each leaf sampling event, three areas were considered to image crop in each leaf: bottom, medium third and tip, both for IL and OL (Fig. 2). The leave image is divided into three equal parts and the 5% of the boundary region is not considered to avoid overlap. At the end, 24 classes were created and 50 images were obtained for each of these classes. Therefore, each class had images from one area of the leaf for each level o N supply of IL and OL. In this way, there were 40 images for training and 10 for test for each class, and in total, 960 images for training and 240 for test. From each of those scanned area, windows with 80×80 pixels were oriented to the horizontal position (Fig. 3). From each image, windows with 80×80 pixels from specific spots where the deficiency symptoms are clearer were extracted. Such image windows were saved without file compression.

According to Zúñiga (2012), color and texture are the main visual characteristics associated to maize nutrition. The following methods proposed by Zúñiga (2012) for AVS were tested in the present study for the texture analysis: Volumetric Fractal Dimension (VFD), Gabor Wavelet (GW) and VFD with canonical analysis (VDFCA).

The VDF works with binary images but was adapted here to work with the images captured by the scan, as proposed by Backes et al. (2009), in which the image signature is calculated to work with all r∈E values, where E is the set of Euclidean distances for a maximum radius r_{max}. In such method the radius ranged from 1 to 20.

$$E = 1, \sqrt{2}, \sqrt{3}, \ldots, r_{max} \quad (2)$$

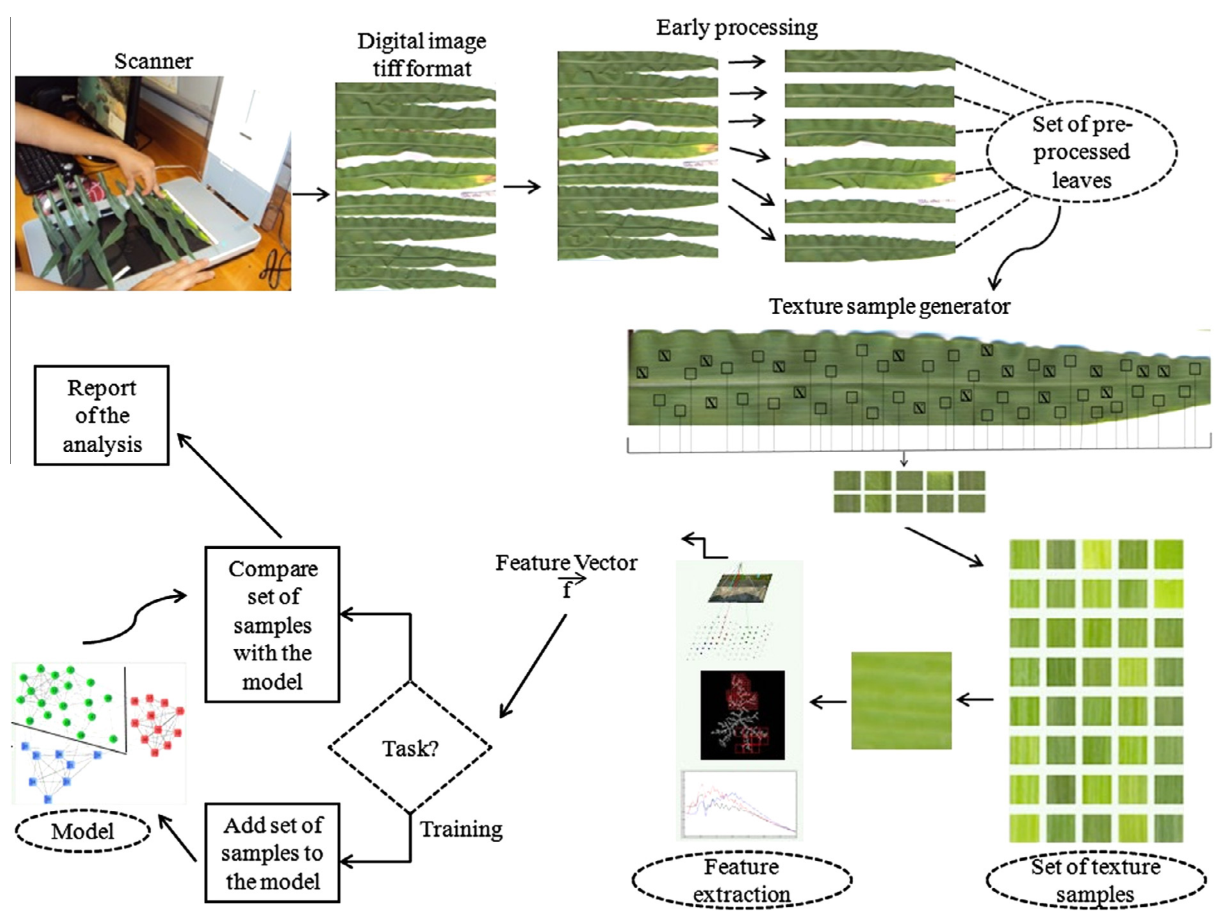

Fig. 1. Image analysis procedure used in this study.

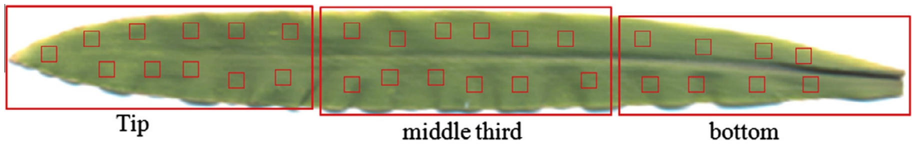

Fig. 2. Separation of leaves for leaves for image analysis considering three parts: tip, middle and bottom.

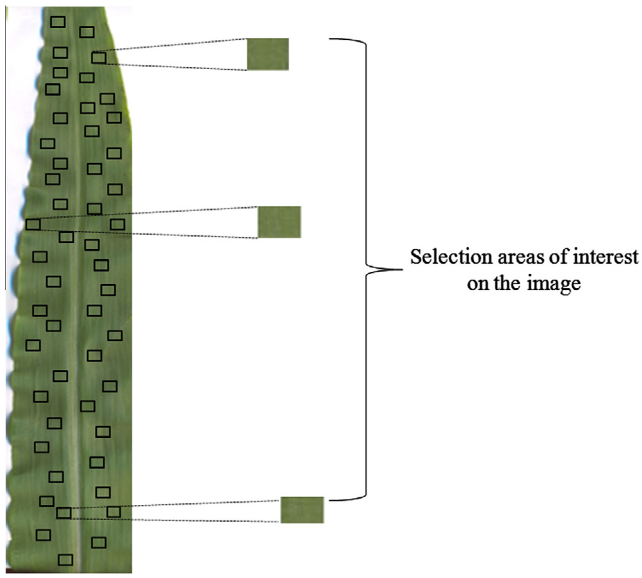

Fig. 3. Segmentation process.

$$\mho(r_{\max}) = [\log\ V(1), \log\ V(\sqrt{2}), \log\ V(\sqrt{3}), \ldots,\ V(r_{\max})], \tag{3}$$

The Gabor bi-dimensional transform is a bi-dimensional gaussian function modulated into a senoidal oriented with a certain frequency W and in certain direction θ. Its bi-dimensional form in the space domain $g(x,y)$ and frequency $G(u,v)$ is given by the following equations:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] + 2\pi jWx \tag{4}$$

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right]\right. \tag{5}$$

The Gabor transformed can be adapted as a wavelet. In such a case these equations are used as a mother wallet. In the next step, a filter dictionary can be obtained by dilation and rotation and $gz(x,y)$ through the function generated as proposed by Manjunath and Ma (1996):

$$g_{mn}(x,y) = a^{-m} g(x',y') \tag{6}$$

where $a > 1$ and m, n refers to the scale and orientation, with $m = 0,1,\ldots, M-1 en = 0, 1,\ldots,$ N – 1 M is the total number of scales and N is the total number of orientations.

For all methods the Naive Bayes classification and the cross validation learning method were used. For the evaluation, the samples were separated randomly into n groups of roughly equal size and was made "to let an outside group" the cross-validation which can also be called a "n-fold cross-validation" test scheme. Samples were independent for each class, and these samples did not appear in the same training and testing. In each processing, 80% (960 images, 40 images per class) of the images were used for training and 20% (240 images, 10 per class) for testing "blind". The confusion matrices were generated to assess the amount of right classifications made by AVS, and also to know classes that were difficult to classify. In addition, were assessed the percentage of images correctly classified or Global Percentage of Right (GPR) and Kappa index (K). According to Everitt and Dunn (2001), the Kappa index indicates the correlation between GPR and truth. This index is used in this study to measure the confidence of classification. The Kappa index is evaluated as follows: 0–0.2: not trust; 0:21–0:41: low; 0.41–0.60: moderate; 0.61–0.8: trust; 0.81–1.0: worthy trust.

3. Results and discussion

3.1. Visual symptoms

Plants subjected to lack of N showed chlorosis in early leaves which evolved to drying and necrosis. These leaves did not elongate and plants did not evolved (Fig. 4a). Similar symptoms were observed by Ferreira (2012) in the hybrid maize BRS 1010 cultivated in a sand plus vermiculite substrate at 1:1 ratio, in the complete lack of N.

Strong chlorosis in OL, from tip to base and in inverted "V" shape was observed in plants cultivated with 3.0 mMol L^{-1} of N (Fig. 4b). Such scenario evolved to tip drying advancing through the central nervure and finally necrosis and tearing, as well as thin stalks. Such typical symptoms were also observed in plants grown in 40% of N, after the V7 stage.

3.2. Nitrogen in the plant and dry mass yields

From the results obtained, it was found that there were significant effects ($P < 0.01$) of the levels, times and interaction on the nitrogen concentration in index leaves, N accumulated and dry matter yields in shoot and root, with the increment of nitrogen in nutrient solution (Figs. 5 and 6).

The N concentration in IL at the stages V4, V7 and R1 as a function of doses is showed in Fig. 5. It can be observed that the greatest N concentration was observed during the stage V4 with the N dose of 9.0 mMol L^{-1}. For V7 and R1, the maximum concentration of N was around 12.0 mMol L^{-1}. According to Malavolta (2006), adequate levels of N in IL at R1 for maize should be between 28 and 35 g kg^{-1}. The N values at V4 (63 g kg^{-1}) should be related to the fact that leaves are small at this stage, but such value does not relate to N accumulation in terms of dry mass, as can be seem in Fig. 4a which shows that at 24 days (V4) the smallest N accumulations were observed for all doses. According to Büll (1993) the percent content of N in young plant tissues of maize is greater than in the other plant growing stages, although the plant requirement for such nutrient is small due to the short size of the plants.

The V4 stage of development was the time that had lower dry mass yields, with maximum production of shoot and root of 2.84 e 0.96 g $planta^{-1}$ respectively, obtained with the level of N in the nutrient solution of about 10.5 mMol L^{-1}. In V7 was 28.4 g $planta^{-1}$ (shoot) and 12.32 g $planta^{-1}$ (root), obtained with the level of N in the nutrient solution of 13.4 e 10.2 mMol L^{-1}, respectively. The tasseling (R1 development stage) was time that showed the highest biomass yield in the plants, with a maximum of 75.4 g $planta^{-1}$ in shoot and 26.4 g in root, obtained with the

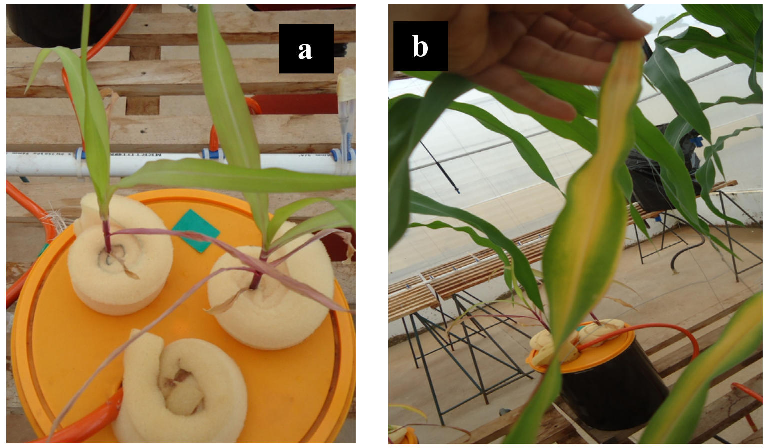

Fig. 4. Nitrogen deficiency symptoms in maize plants subjected to complete lack of N at 24 days after showing (a), and plants grown with 20% N at 35 days after emergency (b).

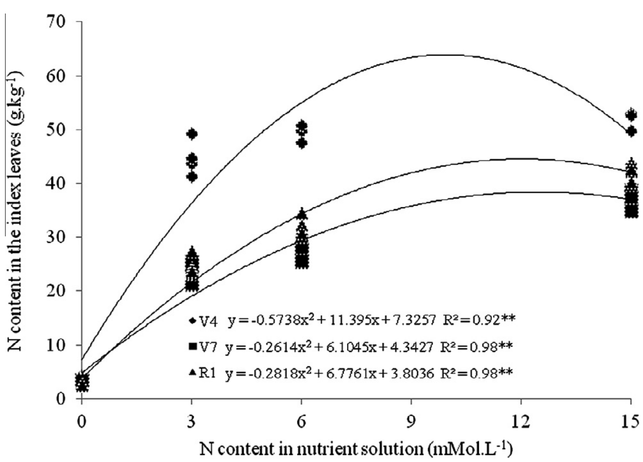

Fig. 5. Nitrogen concentration in index leaves of maize plants submitted to nitrogen levels at different stages of development.

N level in the nutrient solution of respectively 10.4 e 11.15 mMol L^{-1} (Fig. 6a, e and b).

According to the results, it is observed that the omission and reduction of N compromised the dry mass of maize plants during the studied period. The nitrogen content of the plant influences the distribution pattern of carbohydrates within the plant, which affects growth and crop yield, and therefore there is a strong correlation between N content and biomass production (Lawlor, 2002).

Accumulation of N can be observed in the results showed in Fig. 6 in the shoot (c) and root (d). The greatest amount of N was observed at day 66 (R1 stage), in plants cultivated in the full dose of N (Fig. 6c, e and d). According to Coelho (2007), N requirement by plants varies enormously during the growing stages of a plant but reaches a maximum during the beginning of grain formation. Duarte et al. (2003) and Pinho et al. (2009) also reported small N accumulation of N during the initial stages of growth, and a strong increase at 42 days and from 42 days forward a constant and linear increase until the final stages of the development of maize. However, as noted in the dry matter yield (Fig. 6a, e and b), at 24 DAE (V4), the inadequate supply of nitrogen affected the development of corn and consequently the biomass production. According to Coelho (2007), nitrogen deficiency, when the plant has a height of about 20 cm, it will cause reduction in the number of grains, compromising the final production.

3.3. Artificial visual system (AVS)

Tables 1 and 2 are shown the global percentage of right (GPR) and confidence in the classification (Kappa index) for the techniques studied (VFD, GW and VDFCA) for feature extraction in leaves of maize in different stages of crop development (V4, V7 and R1).

Based on the results was observed that the GW technique applied to color images was the one with the best performance, with 82.5% rights for V4 at the bottom of index leaves (Table 1), 87.5% rights for V7 using the image windows at the bottom of old leaves (Table 2) and 98% of rights for R1 using the third middle of index leaves (Table 1). The confidence in the classification (Kappa index) with the use of this technique had an index above 0.91, therefore classified as worthy trust (Tables 1 and 2). According to Table 1 and 2, the GW technique using gray scale had GPR of 94% and Kappa index of 0.99 (worthy trust), but with the use of color images for this same technique, for features extraction, found results even better (GPR 98%). These results confirm the importance of color information in this study in order to characterize the nutritional symptoms on leaves of corn. Similar results were observed by Silva et al. (2014) using the same methods of this study to patterns recognize of nutrient deficiencies for magnesium. The confusion matrices for GW in each growing stage of maize are shown in Table 3.

The confusion matrices show in their diagonal the amount of images that were correctly classified in each set of 50 images. In the lines, it can be seen the amount of images that the AVS assigned to another class (wrong of interpretation).

The confusion matrices of the best results obtained with the bottom of old leaves (Table 3), indicate that the complete omission (zero level) was the simplest class rating, with rights of 96% and 98% for V4 and V7 times respectively, and the class corresponding to the level of 6.0 mMol L^{-1} of N (T3) had the highest wrong of classification in V4 stage. The full level and 3.0 mMol L^{-1} of N (T1 e T2) showed good distinction between them and between other classes. The results also indicate that it is possible to obtain a good separation of classes considering the zero and 3.0 mMol L^{-1} levels, which are the levels of severe and moderate deficiency in the plant. Almost all classes had the greatest number of errors in the T3 class. That can be related to the fact that the leaves in this treatment had images very similar to the full level of N and to the T2 (3.0 mMol L^{-1}) during the V4 stage (Table 3).

It is worth to highlight that the levels 3.0 and 6.0 mMol L^{-1} are the most difficult to be distinguished by the human eye, because

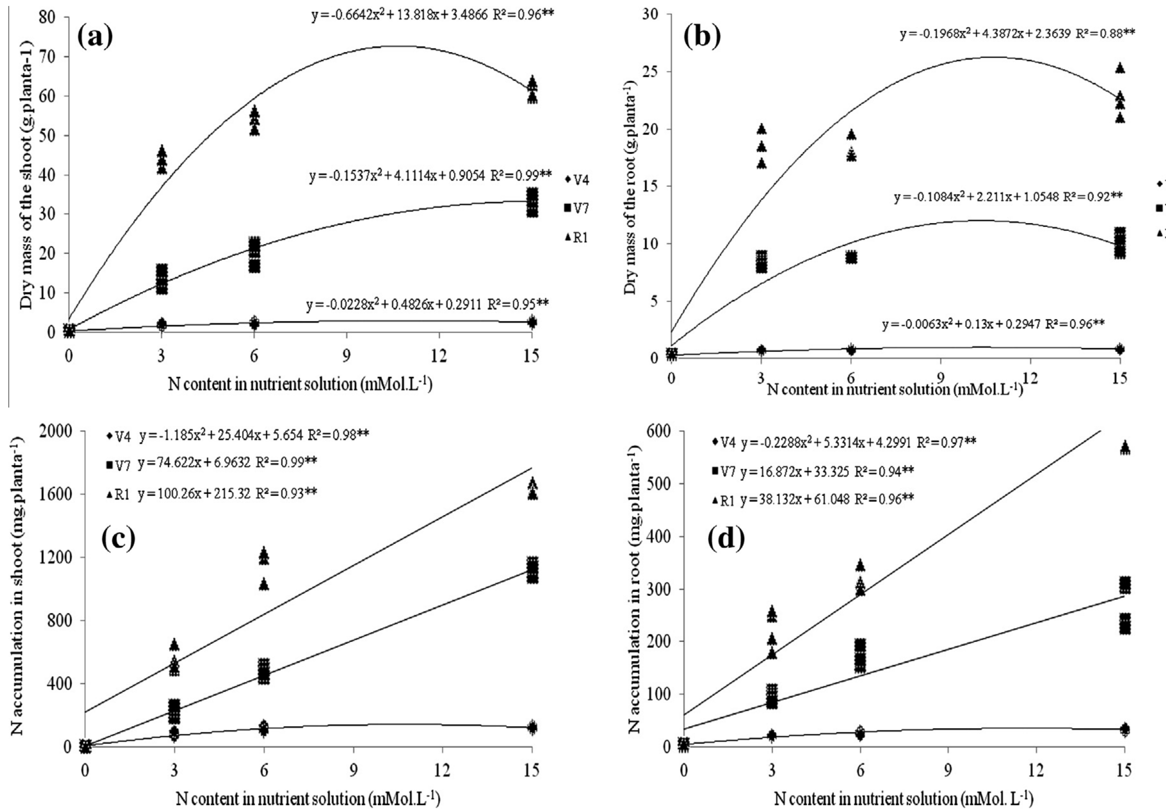

Fig. 6. Dry mass yield in shoot (a) and root (b); nitrogen accumulation in shoot (c) and root (d) of maize plants submitted to nitrogen levels at different stages of development.

Table 1
Global Percentage of Rights (GPR) of color and gray scale images using the techniques Volumetric Fractal Dimension (VFD), VFD with canonical analysis (VDFCA) and Gabor Wavelet (GW), and corresponding Kappa index (K), applied to tip, bottom and middle third (middle) of index leaves of maize plants at stages V4, V7 and R1 grown in different N doses.

	Techniques studied on AVS											
	VFD Color images		VFDCA		GW		VFD Gray scale images		VFDCA		GW	
	V4						V4					
	GPR	K	GPR	K	GPR	K	GPR	K	GPR	K	GPR	K
Tip	70.5	0.87	73.5	0.88	80.0	0.90	64.0	0.85	77.5	0.92	72.0	0.91
Bottom	65.0	0.86	75.0	0.90	82.5	0.95	55.0	0.84	75.0	0.93	71.5	0.91
Middle	65.0	0.87	66.0	0.86	70.0	0.90	52.5	0.79	71.5	0.88	73.5	0.90
	V7						V7					
Tip	59.0	0.80	79.0	0.93	74.5	0.90	54.0	0.77	70.0	0.87	61.5	0.83
Bottom	50.0	0.76	74.0	0.91	75.0	0.92	53.0	0.77	68.0	0.88	65.0	0.85
Middle	62.5	0.81	70.5	0.89	75.0	0.91	56.0	0.78	70.5	0.88	64.5	0.84
	R1						R1					
Tip	84.0	0.96	86.5	0.95	85.5	0.98	62.0	0.86	85.5	0.95	86.5	0.97
Bottom	96.5	0.99	92.0	0.97	98.0	0.99	74.5	0.89	91.0	0.98	94.0	0.99
Middle	89.0	0.98	84.0	0.93	91.5	0.98	66.0	0.86	82.0	0.94	85.5	0.95

these levels of N are close to the full dose and therefore, the symptoms are less perceptible. Even in such cases, the percent rights were 76% for the 3.0 mMol L^{-1} and 66% for the 6.0 mMol L^{-1}, for OL, which can be considered very promising.

The results in Tables 3 suggest that the detection of N deficiency in the early stages of maize development is possible, and also that a good number of rights can be achieved for the levels T1 and T2, which are the severe and moderate levels of N deficiency. The typical symptoms of N deficiency were obtained with the reduction of nitrogen in the nutrient solution, which allowed the recognition of the nutritional patterns of corn by AVS.

The high number of rights in stage V4 is central to this study, since the early identification of deficiency is essential to allow actions to be taken to rescue the crop from future failure. Although the GW technique applied to color images of V4 had the best performance (bottom of leaves) (Table 1), similar percent of rights was achieved from OL with the same technique (Table 2). These results agree with the literature which describes the symptoms of deficiency appearing firstly in old leaves due to N mobility in plants.

The R1 stage showed the Kappa considered "worthy trust" and better GPR in all parts of plants. The percent of rights is also very close between IL and OL, for the R1 stage (Tables 1 and 2). The AVS results pointing to the IL as having the greatest number of rights can be related to the fact that, with the evolution of phenological stage, there was a better differentiation between classes, which can be correlated with the results observed in deficiency

Table 2
Global Percentage of Rights (GPR) of color and gray scale images using the techniques Volumetric Fractal Dimension (VFD), VFD with canonical analysis (VDFCA) and Gabor Wavelet (GW), and corresponding Kappa index (K), applied to tip, bottom and middle third (middle) of old leaves of maize plants at stages V4, V7 and R1 grown in different N doses.

	Techniques studied on AVS											
	VFD Color images		VFDCA		GW		VFD Gray scale images		VFDCA		GW	
	V4						V4					
	GPR	K	GPR	K	GPR	K	GPR	K	GPR	K	GPR	K
Tip	60.5	0.81	61.5	0.84	74.0	0.94	55.5	0.77	65.5	0.86	61.5	0.83
Bottom	62.5	0.81	68.5	0.87	82.0	0.95	46.5	0.74	73.0	0.90	64.0	0.87
Middle	61.0	0.79	55.5	0.84	80.5	0.94	48.5	0.77	69.5	0.88	66.0	0.86
	V7						V7					
Tip	64.0	0.87	78.5	0.94	73.0	0.92	55.5	0.75	74.0	0.91	62.0	0.85
Bottom	71.5	0.89	84.5	0.94	87.5	0.96	51.5	0.80	78.0	0.93	76.5	0.92
Middle	74.5	0.91	79.5	0.96	79.5	0.96	65.0	0.85	77.5	0.94	82.0	0.94
	R1						R1					
Tip	89.0	0.98	81.0	0.94	85.5	0.96	52.0	0.73	82.5	0.95	74.5	0.93
Bottom	77.0	0.93	76.0	0.91	92.0	0.97	49.0	0.72	73.5	0.92	76.0	0.92
Middle	77.5	0.92	75.5	0.90	83.0	0.97	39.0	0.67	72.5	0.90	76.0	0.88

Table 3
Confusion matrix of classification result from bottom of old leaves at stage V4 and V7, and index leaves at R1, of maize grown in different N doses.

Real classification	% Rights											
	V4				V7				R1			
	T1	T3	T3	T4	T1	T2	T3	T4	T1	T2	T3	T4
T1 – 0 mMol L^{-1}	**96.0**	2.0	2.0	0.0	**98.0**	2.0	0.0	0.0	**98**	0.0	0.0	2.0
T2 – 3 mMol L^{-1}	0.0	**76.0**	24.0	0.0	0.0	**68.0**	30.0	2.0	0.0	**98**	2.0	0.0
T3 – 6 mMol L^{-1}	8.0	36.0	**56.0**	0.0	0.0	0.0	**90.0**	5.0	0.0	0.0	**96**	4.0
T4 – 15 mMol L^{-1}	0.0	0.0	0.0	**100**	0.0	6.0	0.0	**94.0**	0.0	0.0	0.0	**100**

Bold numbers mean percentage of rights within their respective classes corresponding to the N doses.

symptoms in plants, with reflections on the development and nutrition of corn at this stage. It is noteworthy that for maize, R1 is the time that best reflects the nutritional status of the crop, so that the index leaves this stage are drains for grain filling, and is the standard leaf for analytical determinations for nutritional diagnosis.

The results presented here point to the AVS using the GW method on color images as being the best for the N status in maize plants, particularly the IL at V4 stage (82.5%) corresponding to early development stage of corn, but still requiring field trials to validate such result.

4. Conclusion

Maize plants replied to N levels with respect to symptomatology, N concentration in plant tissue and biomass production.

The best method for feature extraction in leaves of maize was Gabor Wavelets in color images. The AVS was able to identify the induced levels of nitrogen deficiency in the early stages of development of corn, so that the bottom of index leaves showed of global percentage of right (GPR) of 82.5% at V4 stage and 87.5% in the bottom of old leaves at V7. However, the middle section of the index leave at the R1 stage was the best GPR (98%) to detect the symptoms of nitrogen deficiency by AVS.

The main idea presented in this work could be adopted for others plants, but it should be pointed out that the performance of the system is valid for the conditions under which this experiment was conducted.

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