Seed Assessment Using Fuzzy Logic and Gas Discharge Visualization Data

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Abstract

Assessment of sowing material is a significant concern in seed science. A promising tool for assessing seed material is Corona Discharge Photography or Gas Discharge Visualization (GDV). In this study, this tool was applied to determine relationships between sowing material characteristics and GDV parameters; an Adaptive Neuro-Fuzzy Inference System (ANFIS) was utilized to interpret the experimental data. By using ANFIS, a three input fuzzy inference system was constructed to define the contiguous relations between GDV parameters (i.e., glow area and shape factor) and root length.

Keywords: sowing material, Corona Discharge Photography, Gas Discharge Visualization, Adaptive Neuro-Fuzzy Inference System

1. Introduction

Assessment of sowing material is a significant concern in seed science. One of the most promising tool for assessing seed material is Corona Discharge Photography (CDP) or Gas Discharge Visualization (GDV) (Bankovskii et al., 1986) which is based on the Kirlian photography method (http://en.wikipedia.org/wiki/Kirlian_photography). Gas Discharge Visualization allows for the evaluation of luminescence that arises near the seed surface when placed in a high tension electromagnetic field. Currently, this tool has numerous applications in industry and biophysics research (Ciesielska, 2009; Kostyuk et al., 2011; Korotkov & Krizhanovsky, 2004; Korotkov et al., 2012; Opalinski, 1979; Pehek et al., Root, 1990; Vainshelboim & Momoh, 2005).

The first seed material laboratory experiments using the Kirlian photography method were carried out in the late 60s in Alma-Ata, Russia (Inyushin et al., 1968). The results of examining wheat grain found that the glow of sprouted grain increased sharply compared to the glow of dry grain. Buadze et al. (1989) investigated the effects of the herbicide 2,4-D on the physiological state of 7day old maize seedlings. These researchers documented the changing characteristics of Gas Discharge Images (GDI) of sprouted grain. Maximum intensity shifts in GDI parameters were fixed in the wavelength range of 350 to 450 nm. Borisova et al. (2009) studied the effect of microwave treatment of rape, barley and wheat seed using GDV. Research has shown that the glow intensity of sprouted grain was related to germination potential. Priyatkin et al. (2006) investigated the ability of GDV to characterize wheat grain with no visible signs of injury. This grain was divided into three groups: 1) healthy, 2) grains with mild internal damage from the Fusarium spp. pathogen, and 3) grain with severe internal damage from this pathogen. It was noted that healthy grain was characterized by GDV maximum values for brightness distribution, shape factor and three-dimensional fractal characteristics in comparison to seed subjected to stress.

A more recent method for interpreting complex experimental data is the use of an Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993). Recently ANFIS has been successfully applied in the assessment of several agricultural problems (Akbarzadeh et al., 2009, 2009a; Arkhipov et al., 2008; Atsalakis & Minoudaki, 2007; Azamathulla et al., 2009; Cai et al., 2004; de Araújo & Saraiva, 2003; Krueger et al., 2010, 2011; Kurtener et al., 2005; Marce et al., 2004; Ostrovskij et al., 2014; Peschel et al., 2002; Tooy & Murase, 2007; Xie et al., 2007). The objective of the current study is to ultilize ANFIS for assessing seed using Corona Discharge Photography data.

2. Materials and Methods

2.1 Experimental description

Seed samples from European spruce (Picea abies L.) were gathered in the Leningrad region of Russia (Fig. 1). One seed was placed in each well of a 96-welled plate (Fig. 2). For studying the gas discharge glow from seeds, we used a GDV Camera system to record images for analysis via ANFIS (http://ktispb.ru/en/gdvinstruments.htm#Camera). An example seed glow can be seen in Figure 3. Analysis of changes in discharge images (GDI) included calculations of amplitude characteristics, as well as geometry, brightness, fractal, and stochastic characteristics. These calculations were conducted using the GDV Scientific Laboratory software (http://ktispb.ru/en/gdvsoft.htm#SciLab). After testing with the gas discharge visualization method, the seeds were germinated for 15 days and root length was measured daily.

Fig. 1. A representative sample of European spruce (Picea abies L.) seeds used in this study.

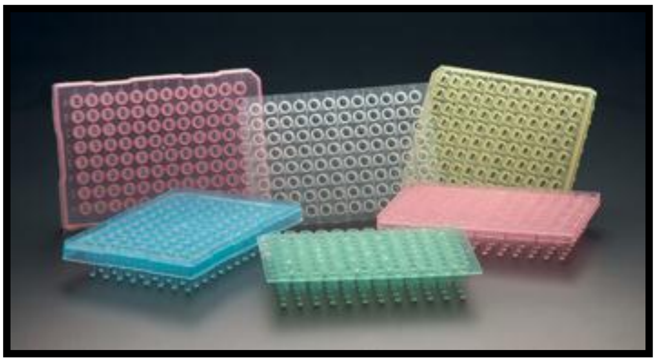

Fig. 2. A picture of the 96-well plates used in this study.

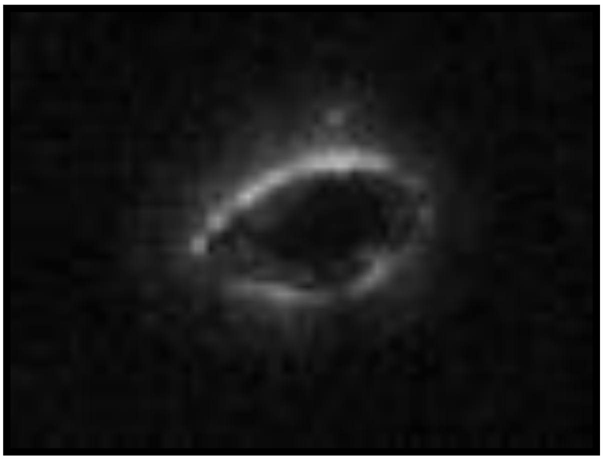

Fig. 3. A sample image illustrating the glow emitted from seed in a high tension electromagnetic field.

2.2 Experimental data processing

To study the relationship between the root length of sprouted grains and GDV parameters, we utilized an Adaptive Neuro-Fuzzy Inference System (ANFIS). A detailed description of ANFIS and its applications for studying agricultural problems has been reported by Jang (1993) as well as by several previously listed publications. As a tool for generating ANFIS, we used MATLAB's Fuzzy Logic Toolbox (FLT) (http://www.mathworks.com/) which enables the creation and editing of Fuzzy Inference Systems (FIS), manually or automatically driven by the data.

To define the contiguous relations among GDV parameters and seed characteristics (e.g., root length), we selected two GDV parameters: Glow area and Shape factor.

Also, the experimental data was divided into parts for fuzzy inference testing. The first part was used for the learning process while the second part was required for the testing process. Data for the testing process is presented in Table 1 and the data for the learning process is shown in Table 2.

Table 1. Data used for the testing process.

Glow area	Shape factor	Root length (cm)
989	3.84	3.50
1223	5.26	4.70
631	6.25	2.50
809	3.56	5.00
874	7.24	4.70
914	5.03	1.60
1297	4.39	2.30
893	6.47	4.20
647	5.21	1.30
964	4.14	3.50

Table 2. Data used for the learning process.

Glow area	Shape factor	Root length (cm)
1262	4.84	4.00
751	5.38	4.30
1194	4.61	1.30
750	4.35	5.50
726	5.80	4.50
492	7.07	5.00
653	8.67	5.50
975	6.26	2.00
1001	5.00	6.00
1387	5.50	6.20
439	9.44	6.50
739	6.24	2.00
794	5.53	1.00
1000	6.33	5.00
777	5.49	4.50
832	6.66	3.30
1357	2.58	3.30
882	3.59	3.90
775	5.40	4.00
1008	3.78	0.20
913	5.44	4.50
1059	4.18	5.30
807	6.02	4.30
1291	3.22	5.00
1087	4.49	1.00
1380	3.84	3.70
1085	5.73	2.50
839	5.24	1.10
1240	3.49	0.50
1056	3.73	3.50
991	4.89	4.20
908	3.92	4.30
588	5.03	2.30
1539	4.29	3.80
1005	4.69	6.00
845	4.01	4.50
703	3.78	3.00
894	5.08	2.70
937	3.90	0.30
897	5.61	1.70
1208	3.98	4.00
854	4.90	4.50
852	5.97	5.00

3. Results and Discussion

By using ANFIS,a three-input Fuzzy Inference Systems (FIS) was constructed to define the contiguous relations among GDV parameters (glow area and shape factor) and root length. Graphical representations of fuzzy modelling results are shown in Figure 4.

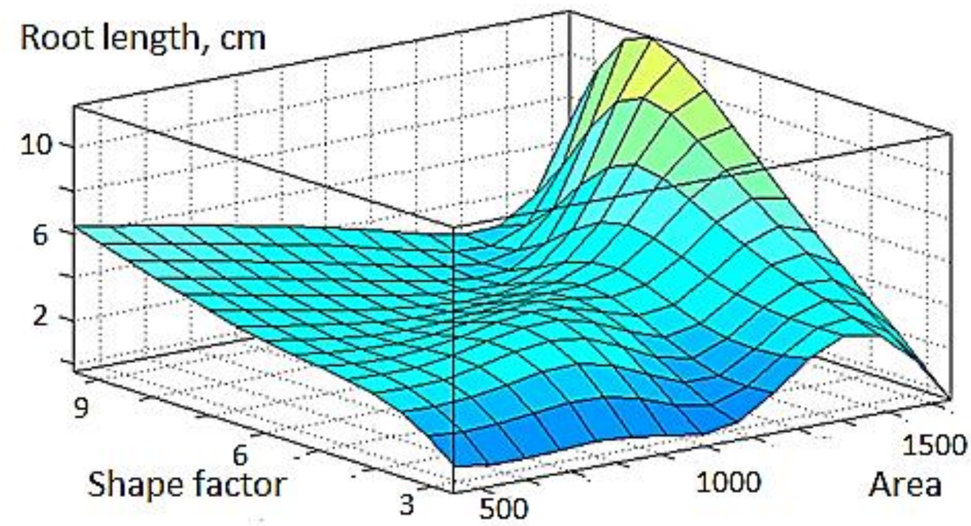

Fig. 4. ANFIS surface after training that describes the relationship between glow area, shape factor, and root length.

The training process and the step-size variations for the input model at each iteration are shown in Figure 5. Usually, the error curve decreases until the end of the training period.

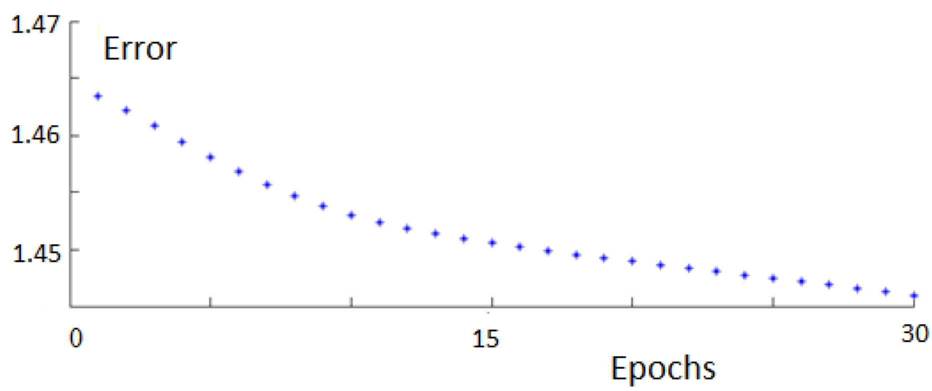

Fig. 5. Error curve generated during the learning process.

The correlation between observed values (dots) and forecasted values (stars) during the testing process is shown in Figure 6.

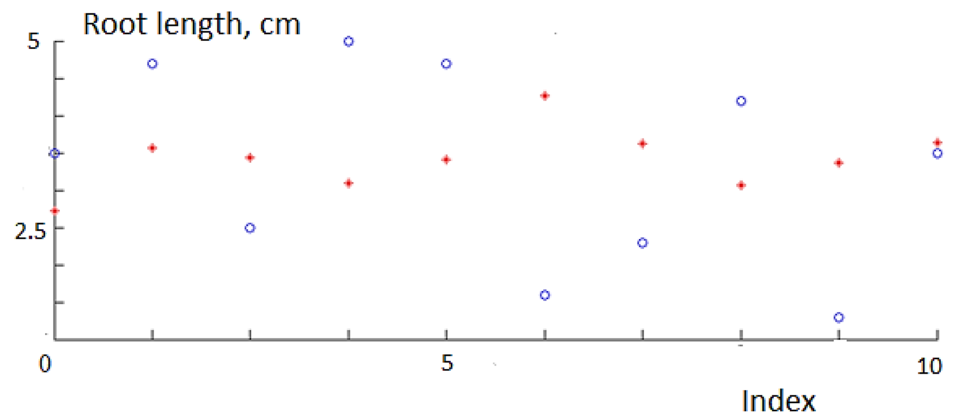

Fig. 6. The correlation between observed values (dots) and forecasted values (stars) during the testing process.

It is important to note that ANFIS was first used to identify the relationship between root length and the GDV parameters. Findings indicated that the first use of ANFIS was successful in constructing a three-input FIS to model the relationship between these parameters. Results of fuzzy modelling are shown in Figure 4. Root length can be considered an indicator of seed quality. This allows us to use the developed FIS (and its graphical representation) for assessing the viability of seed material based on the test data generated from the use of GDV equipment.

4. Conclusion

1. By using ANFIS, a three-input Fuzzy Inference Systems (FIS) was constructed to define the contiguous relations among GDV parameters (glow area and shape factor) and root length.

2. Root length can be considered a good indicator of seed quality. The developed FIS can be used to assess seed viability according to data generated from the use of GDV equipment.

3. The use of ANFIS with more extensive data sets provides an opportunity to obtain future results with lower relative errors.

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