Water and Seed Grading System using Thermal Image

I.Vinothini, R.Swathipriya, B.Gayathri, S.Janaki Raman

Srividya College Of Engineering And Technology

ABSTRACT:

The quality of seeds used in agriculture and forestry is tightly linked to the plant productivity.Thermal images,or thermograms, are actually visual displays of the amount of infrared energy emitted, transmitted, and reflected by an object. Thermal imaging technology can be used to detect quality levels in seeds based on the radiation from their surface.A Multi SVM classifiers proposed to improve the accuracy of classification.The simulation results shows in MATLAB.

I INTRODUCTION

Availability of high quality seeds is essential for agriculture, horticulture as well as seedling productivity, since the seed quality is tightly linked to the resistance to biotic and abiotic stress, to the germination rate and to the plant performance. The most important input for increasing agricultural production is seed. Image analysis has standard techniques for identification of seed variety, measurement of seed, and acquisition of large amount of quantitative data. Seed testing plays an important role of all other seed technologies. It means that itis a measure of viability and physical factors that regulate use and maintenance of seed. Germinationtest of seed is not alone enough to assess seed quality as vigour test is also required. So that during seed handling operations like extraction of seed information, seed quality, seed viability test is needed. Seed type and quality usually are assessed by visual inspection. But it is not economically good in time and cost wise. Also the varietal identification and classification is not uniform, because it depends on the human ability and with personal circumstances. Issues like eye fatigue, call variations between seed inspectors is owing to human involvement throughout the seed test procedure. This method is adapted to assess physiological disorder of seed stage and for seed maturity. Bruise in seed can also be detected. Likewise,an Image analysis technique includes capturing, pre-processing, interpretation, quantification and classification of seed image.

Thermal imaging method is a subsurface defects or anomalies detection method owing to temperature differences observed on the investigated surface, such as the wind turbine blade, during monitoring by using infrared sensors or cameras. The temperature difference when compared to the sound part is related to the difference of thermal diffusivity and hence indicates material irregularity or damage. Thermal imaging method can be categorized by the thermal excitation method of the test subject using either passive or active methods. The passive approach thermography is used to investigate materials that are at a different temperature than ambient (often higher).

The passive approach is not common in wind turbine SHM and more modifications are required before it becomes a promising method. The active approach uses an external stimulus source such as optical flash lamps, heat lamps, hot or cold air guns to induce relevant thermal contrasts on the test subject One specific type of active thermal imaging method is the thermoelastic stress method, which is developed based on the thermo elastic effect. Thermoelastic effect is the temperature change of elastic solid due to the change of stress . Higher acoustical damping, higher stress concentration and different heat conduction near the defective region are expected, and hence the defective region will have a higher temperature.

Nowadays, thermal imaging has been widely usedin agricultural sector. For example, it has been used forbetter understanding of bruised tissue and automaticbruise sorting. Due to the difference of temperaturebetween healthy and bruised tissue thermal imaging showed the significant difference (Varith*et al*., 2003) Thermal imaging is a potential method for the remotedetection of abnormality in agricultural productsbased on the temperature changes during cooling and heating (Manickavasagan, 2008). Thermal imagingallows us to see the variations in temperaturebecause the amount of radiation emitted by an objectincreases with temperature. It has been used to detectforeign materials in hazelnuts (Meinlschmidt and Margner, 2003) and almond (Ginesu*et al*., 2004).Based on the literature reviews, it can be concludedthat with the aid of modern technology, automateddevice with intelligent computing functions can beused to replace human naked eye in deciding qualityof produce. Therefore, this research aimed to analysethe quality of paddy using thermal imaging approach.

II RELATED WORKS

Rice (Oryzasativa L.) production not only servesas the primary source of income for nearly one billionpeople but also provides the staple food for more thanhalf of the world's population (Dawe*et al*., 2011).Based on the world's projection, the demand for ricewill grow from seven to nine billion by 2050 and toreach ten billion before 2100. Global demand for riceis expected to increase roughly 35% by 2035 (FOA,2002), which requires an additional 116million tonsof milled rice (GRiSP, 2010). The increasing demandfor rice requires improvements in rice production.There are many factors must beconsidered tomaintain high quality and quantity of rice production.In Malaysia, the paddy has been gradedbased onthe Deduction Schedule according to MalaysianStandard MS 84: 1998. It was used by rice millersto give price to the farmer when purchasing paddy.

The total percentage deductions ofweight includededuction of moisture content, immature paddy andforeign material. High moisture directlyreduces theprice of paddy (Belsnio, 1992). Meanwhile, immaturepaddy caused low milling recovery, highpercentageof broken rice, poor grain quality and more chancesof disease attack during storage (Hanibah*et al*.,2014).

A machine vision approach has been used to distinguish two wheat classes (CanadaWestern Red Spring (CWRS) and Canada Western AmberDurum (CWAD)), barley, oats, andrye (Paliwal et al. 1999). Wheat lots will not be at a uniform moisture levelwhen they reachprimary/terminal elevators or other processing facilities. In this scenario, the visual method cannot be used for identifying wheat at different moisture levelsbecause of the subjectivity of themethod. It creates an immense need in the Canadian grain industry to develop a rapid andconsistent method to identify wheat classes at differentmoisture levels. Near-infrared spectroscopy is used in various fields such as animal husbandry, agriculture, and pharmaceuticals. In agriculture, it has been used to determine quality parameters such as protein, starch, moisture content, and oil content of different agricultural commodities such as whole (Delwiche 1998) and ground wheat (Wang et al. 2004b); deoxynivalenol levels in wheat (Petterson and Aberg 2003) and barley (Ruan et al. 2002).

Identification of waxy wheat varieties and differentiating them from partially waxy wheat varieties and wild wheat phenotypes have been performed using this method (Delwiche and Graybosch 2002). It has also been used to determine four different life stages of *Sitophilusoryzae*(L.) (rice weevil) at four different infestation levels in artificially infested CWRS wheat (Paliwal et al. 2004). Armstrong (2006) determined moisture and protein contents of soybean and moisture content of corn by developing a partial least squares (PLS) model using spectra obtained from single kernels.

III PROPOSED SYSTEM

SVMs were mainly proposed to deal with binary classification but in today’s life, w e mostly have huge amount of data which we want to classify. Time series datarepre sent quantities or trace the values taken by a variable over a period such as a month, year etc. Examples are stock market, price indexing etc. In this t here will be morethan two classes. So this creates the need of multiclass classificatio n. Multiclass classification means classifi cation with more than two classes.

Before introducing SVM, we have differentkinds of multiclass techniques. Fi rstly we will distinguish it on the basis of direct and indirect approach (via binary). DirectApproaches includes k-nearest neighbor, decision tree and bayes classification, linear classifications like perceptron. Multiclass classifications thro ugh binary include One-vs-one and One-vsall, Directed acyclic graph svm, Error co rrecting output codes.Nearest Neighbor cl assifiers are based on closeness. When gi ven an unknown tuple, classifier searches the pattern space for the k training tuple s thatare closest to the unfamiliar tuple. T he k training tuples are the k "nearest neig hbors" of the unknown tuple . Closeness i s defined in terms of a distance metric su ch asEuclidean Distance . Nearest Neighb or classifiers can be extremely slow whe n classifying test tuples . It suffers from p oor accuracy when given noisy or irreleva nt attributes.Euclidean Distance can be cal culated by Decision Tree is a flowchart like structure where each internal node denotes a test on an attribute, every branch represents as a result of the test and each leaf node holds a class label. The topmost node in a tree is the root node. In classification, attribute values of the tuple are tested against the decision tree. Decision Trees can be easily converted into classification rules. Decision trees are popular because it doesn't require any domain knowledge, parameter setting and can handle multidimensional data with fast speed and good accuracy . Bayes classification predicts class membership probabilities such as probability that a given tuple belongs to a particular class. It is based on bayes theorem. Bayes theorem provides a way of calculating posterior probability (HP / X) of H conditioned on X.

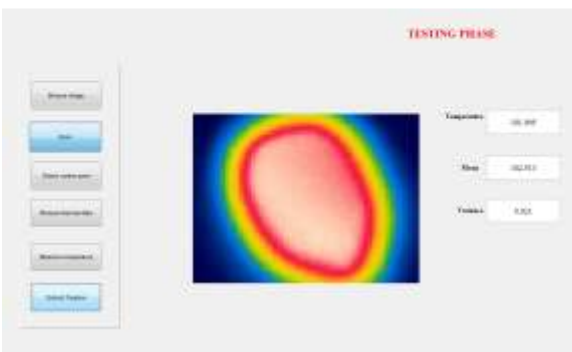
Bayesian classifiers have the minimum error rate in comparison to all other classifiers but in practice this is not always the case sometimes inaccuracies in assumptions such as lack of available probability data [1]. Now let us consider the case Multiclass classification using Binary. In SVM, The idea of using a hyperplane to separate the data into two groups sounds well when there are only two target categories, but how does SVM handle case where the target variable has more than two categories or values? Numerous approaches have been suggested, but there are two most popular approaches described below .

In general, the most frequent method has been to construct one-versus-rest classifiers (usually referred to as ``one-versus-all" or OVA classification) where each category is split out and all of the other categories are merged and to choose the class which classifies the test data with greatest margin. It divides an m class problem into m binary problems. The learning step of the classifiers is done by the whole training data and all other examples as negatives . In validation phase, a pattern is presented to each one of the binary classifiers and then classifier which provides a positive output indicates the output class.

In numerous cases, the positive outcome is not unique and some tiebreaking techniques are compulsory. The most familiar approach uses the confidence of the classifiers to decide the last outcome, predicting the class from the classifier with the maximum confidence. Rather than having a score matrix, when dealing with the outcomes of OVA classifiers (where ir in [0, 1] is the confidence for class.

Matlab implementation results

our proposed thermal image processing system has been coded and implemented using matlab below figure shows output results



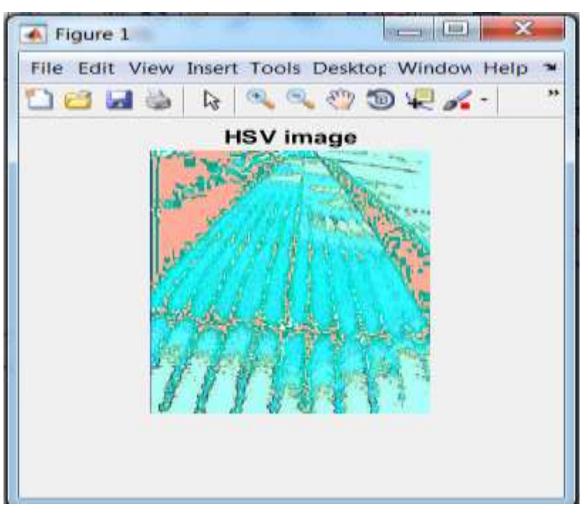
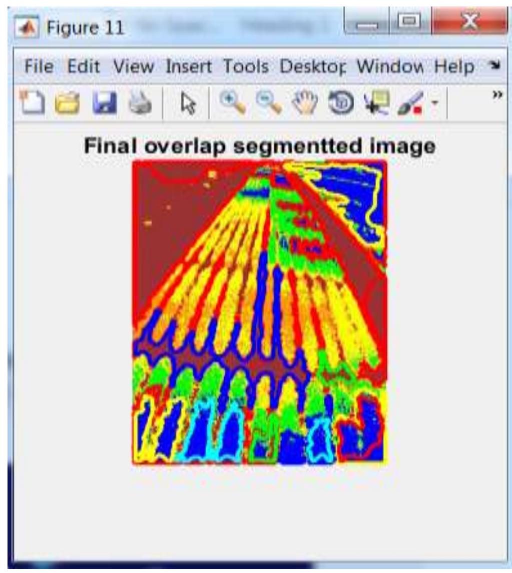


fig thermal seed classification

fighsv of erath image

fig region identification



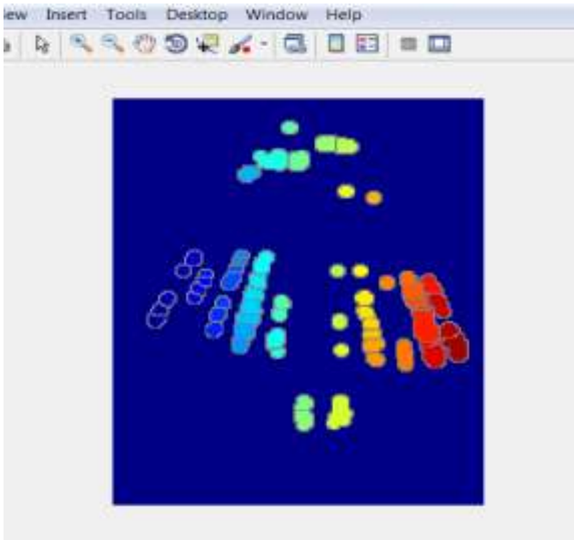


Fig thermal segmented image

Conclusion

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New techniques of determination of paddy grading
parameters namely moisture content, immature
condition and seed classification have been presented
in this paper. The proposed techniques which used
thermal imaging technology gave over higher accuracy
where high moisture content, immature condition
and chaff occurrence were indicated by lower pixel
values. It is also concluded that the determination of the viability (viable,
empty, and infested) of Norway spruce seeds can be predicted with
high accuracy using thermal imaging or hyperspectral imaging
analysis in the SWIR range

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