AUTOMATIC PLANT PEST DETECTION AND RECOGNITION USING k-MEANS CLUSTERING ALGORITHM AND CORRESPONDENCE FILTERS

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ABSTRACT

Plant pest recognition and detection is vital for food security, quality of life and a stable agricultural economy. This research demonstrates the combination of the k-means clustering algorithm and the correspondence filter to achieve pest detection and recognition. The detection of the dataset is achieved by partitioning the data space into Voronoi cells, which tends to find clusters of comparable spatial extents, thereby separating the objects (pests) from the background (pest habitat). The detection is established by extracting the variant distinctive attributes between the pest and its habitat (leaf, stem) and using the correspondence filter to identify the plant pests to obtain correlation peak values for different datasets. This work further establishes that the recognition probability from the pest image is directly proportional to the height of the output signal and inversely proportional to the viewing angles, which further confirmed that the recognition of plant pests is a function of their position and viewing angle. It is encouraging to note that the correspondence filter can achieve rotational invariance of pests up to angles of 360 degrees, which proves the effectiveness of the algorithm for the detection and recognition of plant pests.

KEYWORDS: Automatic Plant Pest detection, pest recognition, k-means clustering and Correspondence filter

INTRODUCTION

Agricultural plants or crop cultivation has seen rapid development in both the quantity and quality of food production, however, the presence of pests and disease on crops has hampered the quality of agricultural produce. If the presence of pests on crops is not checked

properly and an adequate lasting solution provided the quality and quantity of food production will be reduced, as a result there will be an increase in poverty, food insecurity and the mortality rate. This adverse effect can affect any nation's economy especially those where 70% of the population depend solely on the proceeds from the agricultural sector for their livelihood and survival. One major problem for agriculturists is to reduce or eradicate the growth of pests affecting crop yields. From our analysis a pest is any organism that spreads disease, causes destruction or is otherwise a nuisance. The most common pests affecting plants are Aphids, Fungus,Gnats, Flies, Thrips, Slugs, Snails, Mites and Caterpillars. There is therefore a need to detect these pests at all stages of their lifecycle: either at an early or advanced stage and suggest remedies so that much of the damage can be avoided so as to increase crop yields.

Pests cause periodic outbreaks of diseases, which lead to famine and starvation. In recent times across some nations of the world, there are recurrent cases of epidemics as a result of pest infestations, for instance in north eastern India in 1943 there was an outbreak of helminthosporiose pests on rice, which caused a heavy loss of food grains and claimed millions of lives. Since the effects of plant diseases caused by plant pests are devastating, a lot of farmers were discouraged to the point where some decided to abandon crop cultivation. The principal technique or procedure used regularly for the detection and recognition of crop pests by many farmers in major parts of the world according to H. Al-Hiary et al[1] is observation with the naked eye. This method requires continuous monitoring of the crop stems and leaves, which is difficult, labour intensive, inaccurate and expensive for large farms.Jayamala et al[2] listed various methods studied for increasing throughput & reducing subjectiveness arising from human experts in detecting the plant diseases. His work reveals that different methods are used by different researchers for plant disease detection and analysis. The various techniques demonstrated by several authors are thus: H. ZulhaidiMohdShafri et al[3] demonstrated Self-organizing maps & back propagation neural networks with genetic algorithms for optimization & support vector machines for diseases classification. Mohammed Ei – Helly et al[4] uses image analysis integrated with the Central Laboratory of Agricultural Expert System (CLASE) diagnostic model; B. J. Woodford et al[5]identified the rate of browning within Braeburn apples and created an image recognition system to detect pest damagewith the use of a wavelet based image processing technique and a neural network; M. S. Prasad Babu et al[6] illustrated the use of a back propagation neural network; PanagiotisTzionas et al[7]used a combination of morphological features of leaves, image processing, feed forward neural network based classifier &a fuzzy surface selection technique for feature selection; A. Meunkaewjinda et al [8] used a combination of image growing, image segmentation & a Zooming algorithm for the detection of plant diseases; Otsu[9] illustrated segmentation, k-means clustering & back propagation feed forward neural network; RakeshKaundal et al[10] used support vector machines for developing weather based prediction models of plant diseases; H. Al-Hiary et al [11] designed airborne hyper-spectral imagery & the red edge techniques. Yan Li[12] proposed automatic spray a new method of pest detection and positioning based on binocular stereo to get the location information of the pest, which is used for guiding the robot to spray the pests with pesticides but his work did not make provision for invariance to distortion or angular transformation in the orientation of the pests on the crops. If there are changes in the orientation or position of the pests on the leaf, the robot is likely to miss the target and spray on areas not affected by the pest. Paul Boissard[13] demonstrated a cognitive vision approach to early pest detection in greenhouse crops, his work concentrated on low infestation cases, which is crucial to agronomic decision making, particularly on white fly's. It was very good work for early detection of white fly but did not

extend to more complex cases and on all forms or species of the pest, especially when the pest changes position or orientation. Recent research work has dwelled mostly on the detection of different crop diseases; however, Di Cui[14] reported on how various sensing technologies have been developed for automatically detecting crop diseases whereas little or no attention is paid to the fundamental cause or the causal agent of the crop problems. The early detection of crop pests will help to evaluate the effect and the range of the existing pest populations before they become widespread in the environment. This facilitates their destruction by the introduction of predator species or other appropriate integrated pest management techniques, which delivers, according to the United States Environmental Protection Agency[15],acceptable pest levels, preventive cultural practices, monitoring, mechanical controls, biological controls, and responsible pesticide use. Management is frequently contingent on identifying the existence of pest breeds whilst their populations are still restricted in size, it is important to recognize pest infestations before taking any control measure. Prevention of pest invasion is better than curing the effect that the pests have caused.Effective integrated pest management is achieved by having precise knowledge of the different pest species, and the related disease causal agents; having the knowledge of the pest before acting

provides the opportunity to devise a suitable administrative strategy. The eradication of crop diseases has yielded unfavourable results because of incorrect procedures in handling pest control methods. To facilitate viable plant pest control an automatic pest recognition system using k-means clustering in combination with a correspondence filter is investigated. Automatic detection and recognition of plant pests is very important and demonstrates the advantage of maintaining regular surveillance over a large field of crops. Such a system automatically detects the various stages or symptoms of the pest invasion, when they appear on any part of the plants (leaf and stem).

MATERIALS AND METHODS

The automatic plant pests' detection and recognition algorithm presented in this article uses k-mean clustering (see APPENDIX (A)) and the Correspondence filter (see APPENDIX (B)). As a test bed we investigate a collection of plant pests, which were obtained from different online resources, among which are: ALABAMA Nursery and Landscape [16] Maria Iannotti[17] and Paul S. Hamilton[18].Our algorithms have been tested on more than ten crops or plant pests as shown in Figure 1. The proposed algorithm for the pest detection and recognition flow chart is depicted in Figure 2. The proposed pest detection and recognition algorithms can be divided into two phases, the detection phase and the recognition phase.
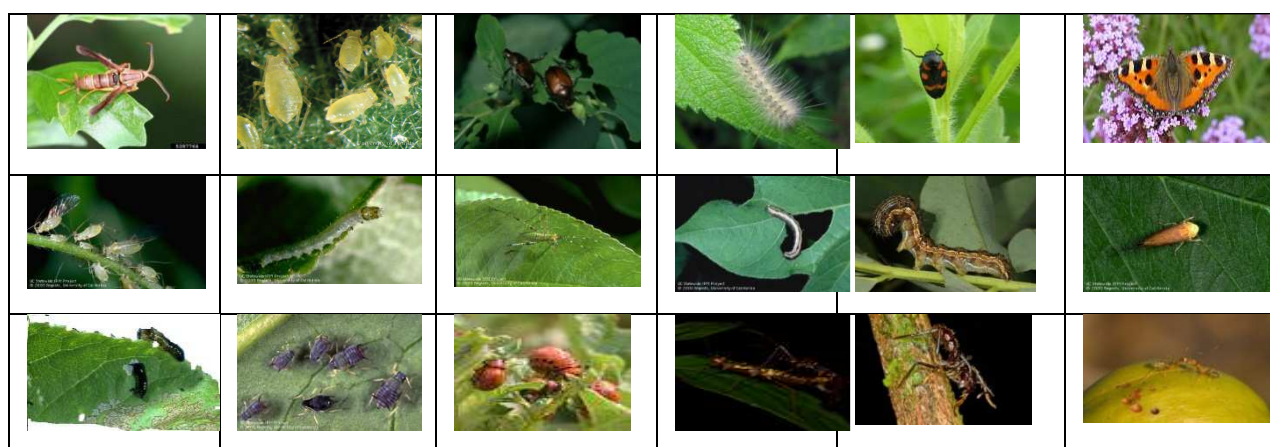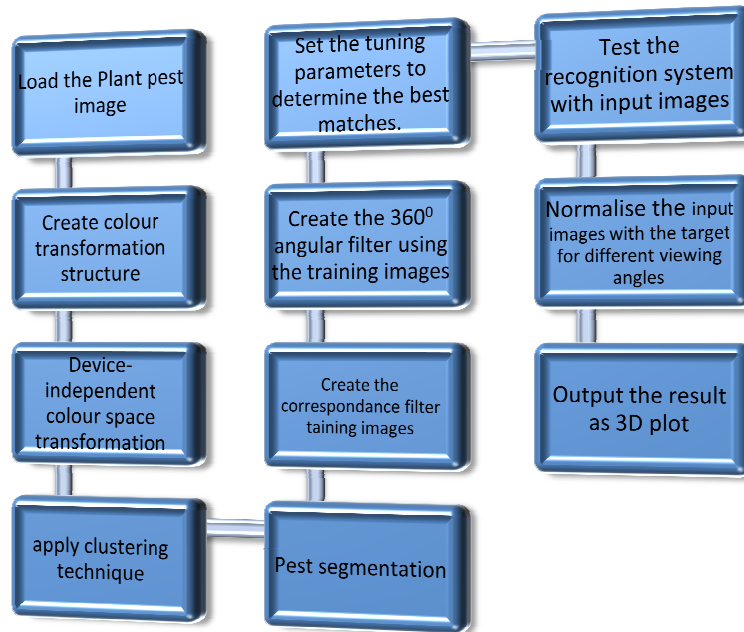
Figure 1: Pests in their habitats

Figure 2: Proposed plant pest detection and recognition process flow chart

The algorithm starts by acquiring the digital image from the environment and loading them as the filter construction images, following acquisition the colour transformation structure for the RGB plant pest images was created. A device-independent, L*a*b* (abbreviation for the CIE 1976 ($L*$, $a*$, $b*$) (or CIELAB), which consists of luminosity L*, chromaticity layer a* and chromaticity layer b*, which houses all the colour (red-green and blue-yellow axis information) colour space transformation structure was applied; the k-means clustering technique was then used to segment the plant pest images. Now the object(s) or pest segmentation process begins by identifying the principally green colour pixels based on using a varying threshold estimate, all the red, green and blue colour components of the pixel that are below the set threshold are assigned a zero value, so that all the pixel intensities that are less than the threshold value are discarded.This technique is applied in as much as we presume that, these pixels are not useful for the pest identification. All the pixels on the boundaries of the object cluster and all the colour pigments, which are designated zeros, were deleted and the segmented pest result is shown in Figure 3. The same steps were repeated for each pest image in the data set. The second stage of the algorithm begins by angle multiplexing the pest detected from the k-means algorithm into the correspondence filter at 5^0 increments. The recognition process was then initiated using the constructed correspondence filter.

Figure 5a,Figure 6a and Figure 7a display some input images; the output images from the

correspondence filter are normalized as a 3D plot and displayed in Figure 5b, Figure 6b and 7b . The peak of the matrix occurs where the pest images are best correlated yielding a maximum correlation height, equivalent to +1.0 and above. The results reported by Figure 5, 6, and 7 show accurate matching between the input images processed using the k-mean clustering algorithm and the correspondence filter training images. The results confirmed the presence of homogenous and similar objects, which proves that the pest detection and recognition algorithm is working effectively. The reliability of the algorithm is shown to be excellent as the filter can respond to in-plane distortion of the pests from 00 to 3600.
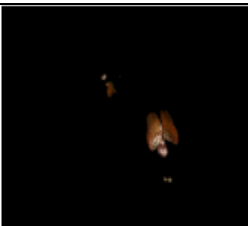
RESULTS

Pests in their habitats	Detected pest	Pests in their habitats	Detected pest
(a)	(a)i	(c)	(c)i
(b)	(b)i	(d)	(d) i

Figure 3: Original input image and the detected pests

Figure 3(a) to (d) illustrates the original input pests in their habitat and (a)i to (d)i illustrates the detected pest segmented from the plants or crops.

The correspondence filter has been tested precisely for its detection and recognition accuracy especially for its distortion invariance ability. A subset of the training image data base is shown in figure 4. The sub-database is made up of 10 training images rotated in plane by five degree increments between each training image of the: grape root borer (line1), cowpea aphids(line2) and Japanese beetle (line3).To optimise the recognition performance of the correspondence filter, suitable values of the tuning parameters alpha, beta and gamma had to be selected. The values of these parameters were picked by observing the impact of different values for a number of trials until the most appropriate value that yielded the best recognition ability was established. For these correspondence filters the tuning parameters chosen were α= 0.0000009; β= 0.45 and Y= 0.1. The training images that were used are shown in Figure 4 (line 1, 2, and 3) their rotation increments in steps of 50 from 00 to 450. Each of these training images were used to create the correspondence filter and the results of correlating the input images with the correspondence filter are shown in Figure 5, Figure 6, and Figure 7
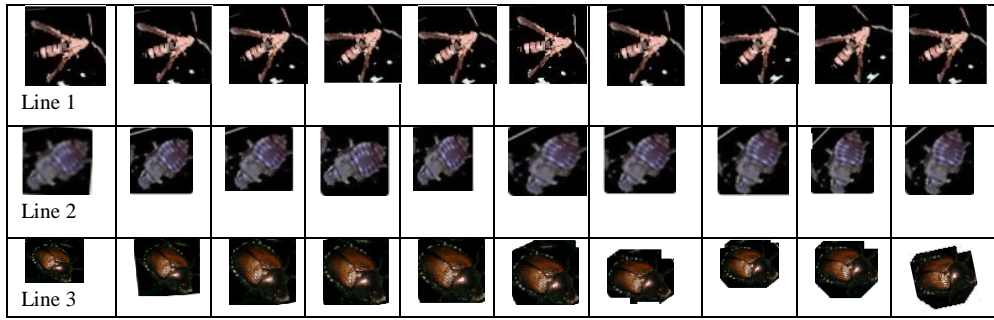
Figure 4: Samples of the training image data base

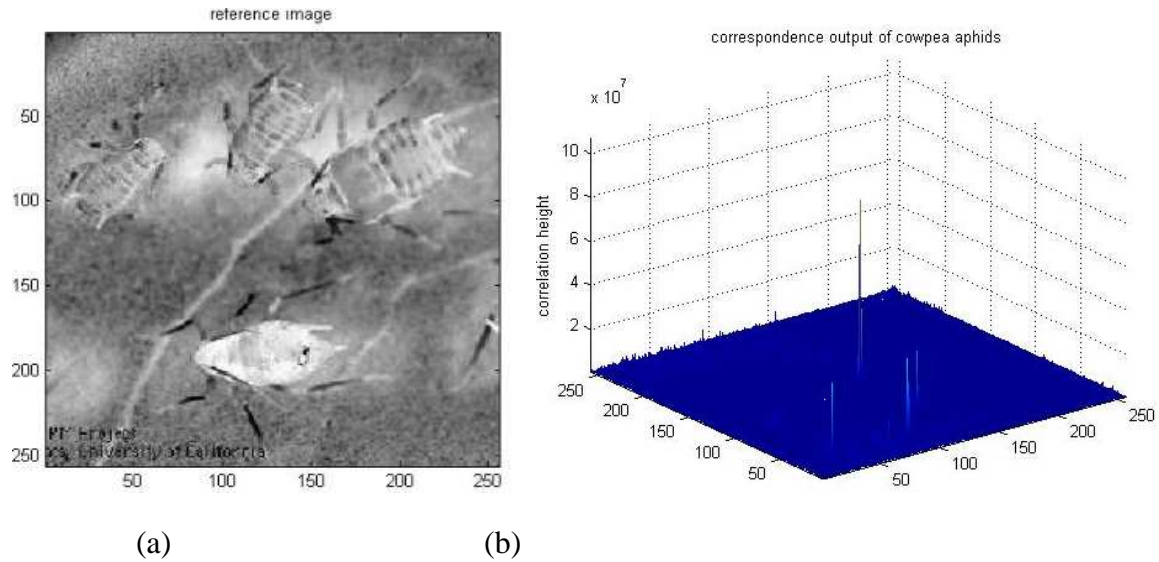

(a)   (b)

Figure 5: Output from the correspondence filter for the cowpea aphids

Figure 5(a) shows the original input image of the cowpea aphids. A subset of the correspondence filter training images are shown in figure 4 line 2, The target training images are shown at various rotation angles , the output from the k-means algorithm at different angular rotations was used for construction of the correspondence filter, using this training set the filter is able to recognise matches with the input image. The result of the matches is illustrated Figures 5b, Figure 6b and Figure 7b where the recognition output from the Correspondence filter is displayed as a 3D plot that is optimised by the tuning parameters: alpha, beta and gamma.

ALGORITHM RELIABILITY
The reliability of the correspondence filter is shown by the ability of the filter to detect and identify the number and position of bugs in the input images. For instance the input image of the cowpea aphids of   Figure 5(a) shows the presence of four bugs on the plant and the 3D plot of the same figure 5(b) also confirmed the recognition and position of the number of bugs via the number of spikes. Figure 6b displayed two spikes as there are only two Japanese beetles on the plant and Figure 7b shows only one spike to confirm the presence of only one bug in the input image of the grape root borer. The result of Figure 8was obtained using the tuning parameters: α= 0.0000009; β= 0.45 and Y= 0.1, for the Japanese beetle it illustrates the reliability and the invariance of the correspondence filter to respond to all the distorted images of the pests at different positions from 00 to 3600, Figure 8 demonstrates the filter's response for 450 of rotation, the curve shows an upward trend with the bug rotation

(a)   (b)
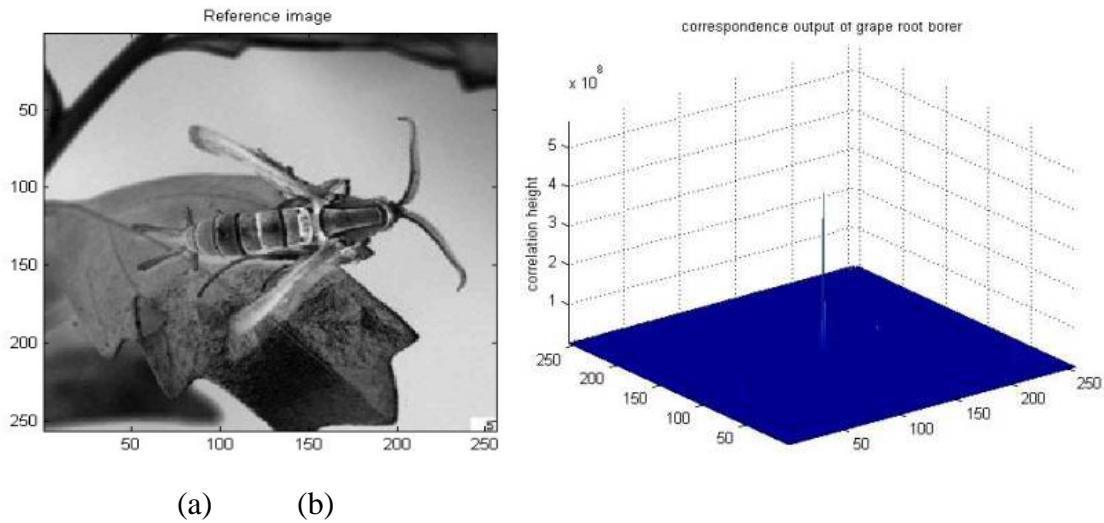
Figure 6: Output from the correspondence filter for the grape root borer

(a)   (b)
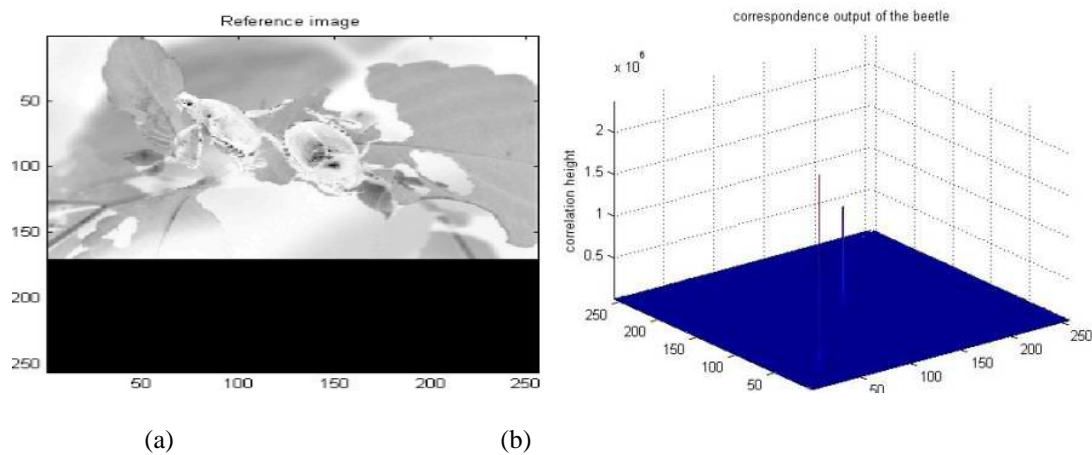
Figure 7:   Output from the correspondence filter for theJapanese beetle

The same processes were applied for the different data sets and the algorithm was able to prove its reliability in the detection and recognition of the various in-plane distortions of the different species of pests illustrated in Figure 1.

	0	5	10	15	20	25	30	35	40	45
☐	1.369	1.382	1.374	1.377	1.381	1.382	1.431	1.416	1.41	1.42

Figure 8: The distortion invariant response of the Japanese beetle

CONCLUSION

In this paper, we apply k-means clustering and correspondence filtering for clustering and identification of the plant pest respectively. Detection and recognition of the pest is the main goal of the proposed technique. Thus, the algorithms were measured to check their performance on several pl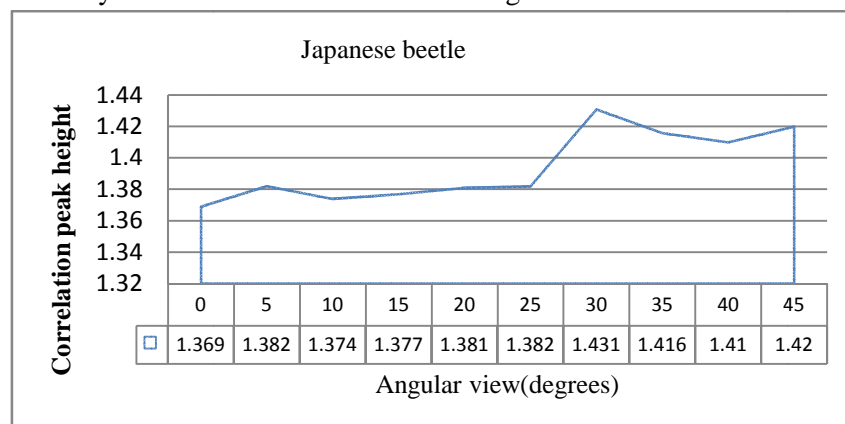ant pests as shown in figure 1. The experimental results demonstrate that the proposed method is a useful technique, which can sustain exact detection and recognition of Plant pests in their various shapes, sizes, positions, and orientations using computationally efficient algorithms. The expansion of this research will centre on advanced hybrid algorithms that will be able to count and display the number of pests found on any crop or plant. We will use the correspondence filter to increase the pest identification rate of the overall classification procedure and we shall devote our future research to automatically calculating the severity of the detected pest infestation and focus individually on the detection of the pest at the different stages of its life cycle

APPENDIX (A)

Plant pest datasets are so large that direct manipulation is impractical. Some method of data consolidation is required first to reduce the size of the dataset without losing the essential features of the image. All consolidation methods sacrifice some detail as expressed by Vance Faber et al[19]; the most desirable methods are computationally efficient and yield practical application results that represent the original data.This paper uses the k-means clustering algorithm developed at the Laboratory specifically for clustering large plant pest datasets.Clustering involves partitioning a set of data points into non-overlapping groups with similar characteristics or some measure of proximity. When a plant pest dataset is clustered, every point is assigned to some cluster, and every cluster can be characterized by a single reference point, usually an average of the points in the cluster.

However, the main purpose of clustering a plant pest dataset is to reduce the size and complexity of the dataset, which is accomplished by replacing the coordinates of each point in a cluster with the coordinates of that cluster's reference point. A clustered dataset requires less storage space and can be manipulated more quickly than the original dataset.

When clustering is done for the purpose of data reduction, as in the case of the Plant pest images, then iterative-partitioning algorithms are most suitable, the goal is not to find the best partitioning but we want a reasonable consolidation of N data points into k clusters as demonstrated by Vance Faber[19].

Iterative algorithms begin with a set of k reference points whose initial values are usually chosen by the user. First, the data points are partitioned into k clusters: A data point x becomes a member of cluster i if z_i is the reference point closest to x.

The positions of the reference points and the assignment of the data points to clusters are then adjusted during successive iterations, J. MacQueen[20].

Conceptually, the initial partitioning is set up as described above: All the data points are partitioned into k clusters by assigning each point to the cluster of the closest reference point. Adjustments are made by calculating the centroid for each of those clusters and then using those centroids as reference points for the next partitioning of all the data points. It can be proved that a local minimum of the error measure E corresponds to a "centroidalVoronoi" configuration, where each data point is closer to the reference point of its cluster than to any other reference point, and each reference point is the centroid of its cluster. The purpose of the iteration is to move the partition closer to this configuration and thus to approach a local minimum for E, Vance Faber et al[19].

$$E = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \|x_{ij} - z_i\|^2 \qquad \text{Eqn. 1}$$

where x_{ij} is the jth point in the ith cluster, z_i is the reference point of the ith cluster, and n_i is the

number of points in that cluster. The notation $\|x_{ij} - z_i\|$ stands for the distance between x_{ij} and z_i. Hence, the error measure E indicates the overall spread of data points about their reference points. To achieve a representative clustering, Vance Faber *et al* said E should be as small as possible. The error measure provides an objective method for comparing partitioning as well as a test for eliminating unsuitable partitioning, the original concept of the algorithm as a method of clustering data over a continuous space. In his formulation, the error measure E_i for each region R_i is given by J. MacQueen[20]

$$E_i = \int_{x \in R} \rho(x)\|x - z_i\|^2 \, dx \qquad \text{Eqn. 2}$$

where $\rho(x)$ is the probability density function, a continuous function defined over the space, and the total error measure E is given by the sum of the E_i's.

APPENDIX (B)

Correspondence filters have been extensively used in the world of detection and security. Their ability to discriminate objects from cluttered backgrounds makes correlation a very powerful tool that can be used for demanding, real time applications. Correspondence filters are known for their shift-invariance and distortion tolerance, which makes them suitable and attractive for pest pattern recognition applications.

The correspondence filter is a powerful algorithm with the following three important features:

(a). The ability to control the correlation peak localisation. (b). Good distortion tolerance. (c). The ability to suppress noise/clutter.

In this paper we will use the correspondence correlation filter in the frequency domain, it has a transfer function given by A. Mahalanobis, et al[21]:

$$h = \frac{m_x^*}{\alpha C + \beta D_x + \gamma S_x} \qquad \text{Eqn. 3}$$

where α, β and γ are the filter non-negative

parameters, m* is the average of the training images (in the frequency domain), C is the additive noise and D_x is the diagonal average power spectral density of the training images defined as:

$$D_x = \frac{1}{N}\sum_{i=1}^{N} X_i^* X_i \qquad \text{Eqn. 3}$$

S_x is the similarity matrix of the training images and defined as:

$$S_x = \frac{1}{N}\sum_{i=1}^{N}(X_i - M_x)^*(X_i - M_x) \qquad \text{Eqn. 5}$$

where X_i is a diagonal matrix of the i_{th} training images.

Since the correct information for the additive noise value (*C*) is not available at all times, several methods have been used to estimate and set the optimal value of the additive noise input to the filter design. The most common method is the use of the white noise covariant matrix by H. Zhou et al[22] as given below:

$$C = \sigma^2 I \qquad \text{Eqn. 4}$$

where σ^2 is the variance and *I* is the identity matrix. He further stated that other methods use an image as the added noise/clutter, which usually results in a better correlation performance. A power spectrum density technique has also been used in other filters to set the additive noise value as demonstrated by S. Tan et al[23]. We therefore use image informa-tion such as standard deviation and the mean to set the additive noise value, Kypraios et al[24].

The input image statistical information, the variance and mean are used to set the value of the additive noise in the filter design. The *C* value according to Ahmad T. Alkandri et al[25] is given as:

$$C = \sigma/\mu \qquad \text{Eqn. 5}$$

where σ is the input image standard deviation and μ is the same image mean. It is also called the coefficient of variation, a good value of the additive noise is in the range between 0 and 1. Usually, The parameter α will adjust the C value

to give the best correlation result, but in this case the filter will adjust itself so α will be equal to 1. A great deal of research has been done to optimize the tuning parameters or to set the additive noise as described by O. Johnson et al[26]. The parameters will be in the range between 0 and 1. The new technique will minimize the search value that lies between 0 and 1 by selecting the best starting point and also by setting α = 1 will leave us with only two parameters, β and γ to change in order to get the best correlation output.

The test has also shown the direct effect of the new technique on the, β value were it stays stabilized and fixed at 0.1 throughout the test. The new technique optimizes the filter to leave us only with γ to shape up the correlation peak result. It has given the filter a great automation advantage and faster processing time with less parameters to adjust.

MEASUREMENT METHOD

Several measures have been used to quantify the correlation filter performance Kumar, et al[27] which are as follows:

(a) Peak-to-side lobe ratio (PSR).

(b) Peak-to-correlation Energy (PCE).

PEAK-TO-SIDE LOBE RATIO (PSR)

This method will provide a measure of the correlation peak quality. The peak height is compared to the surrounding values and is given as:

$$PSR = \frac{Peak - \mu}{\sigma} \text{ Eqn. 6}$$

where μ is the mean and σ is the standard deviation of the correlation plane pixel intensities. It is a common way of describing the peak quality and how good the match is between the target and the input image.

PEAK-TO-CORRELATION ENERGY (PCE)

PCE will measure the correlation sharpness and is given as:

$$PCE = \frac{|c(0)|^2}{\int |c(0)|^2 \, dx} \text{ Eqn. 7}$$

It compares the peak height relative to the correlation plane energy. Low PCE values indicate a better correlation peak output and thus a better detection of the true target.

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