Fruit Image Analysis using Wavelets

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Abstract

This paper contains a description of research carried out by the Department of Information Science and HortResearch in the area of wavelet-based image processing techniques and neural networks to develop a method of on-line identification of pest damage in pipfruit orchards. The results of the project are encouraging and have warranted further investigation into this difficult task.

1.Introduction

One of the more important tasks in the overall domain known as Image Processing (IP) [1] is the task of Image Classification. But one area where this technique has been rarely applied is in the area of horticultural research, specifically for the analysis of damage to pip fruit in orchards with the goal of identifying what pest caused the damage. The solutions to these tasks could become part of a larger computer based system to allow the user to make more informed decisions with the objective of improving the quality of the fruit produced.

Each insect or insect group features specific characteristics that allow it to be identified through the damage it does to the fruit and/or leaves as by-products of its activities e.g. feeding. Once the insect has been successfully identified, the appropriate pesticide can be applied. Thus, as a pilot study, three pests that are prevalent in Central Otago orchards were selected as the candidates for this research: the leafroller, codling moth, and appleleaf curling midge. All the images were in colour, taken at different orientations, lighting conditions, and sometime contained clusters of fruit on the tree rather than individual fruit. Furthermore the damage to the fruit itself was of varying size and shape. Figures 1, 2, and 3 shows examples of the type of images that were taken.

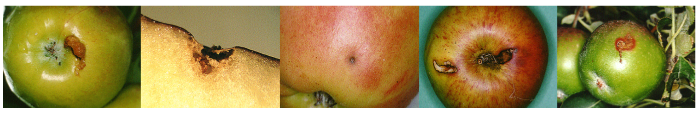


Figure 1: Examples of codling moth damage

To analyse these images, one possible technique could be the use of wavelets to extract the important features required for classification of the damage. In this paper two methods using wavelets are explored to evaluate their applicability to the problem of pest identification.

Figure 2: Examples of appleleaf curling midge damage

Figure 3: Examples of leafroller damage

2.Rationale for using wavelets

Wavelets, developed in mathematics, quantum physics, and statistics, are functions that decompose signals into different frequency components and analyse each component with a resolution matching its scale. Applications of wavelets to signal denoising, image compression, image smoothing, and fractal analysis.

Using Daubechies wavelets for image analysis and comparison has already been shown to be a successful technique in the analysis of natural images [9, 10]. This is because they can characterise the colour variations over the spatial extent of the image that can provide semantically meaningful image analysis

As described in these two papers, the indexing algorithm first converts an RGB colour image into a special colour space, and then applies a fast wavelet transform (FWT) with a special set of Daubechies wavelets for each colour component in the new colour space. The coefficients of the wavelet transform in the lowest few frequency bands, and their standard deviations, are stored as feature vectors. The lower frequency bands normally represent object configurations in the images and the higher frequency bands represent texture and local colour variation.

The whole search is based on the image semantics thus images of the same type will be extracted. For example, given a query image of a windsurfer, other images of windsurfers will be extracted and displayed. This also implied that images of similar damage caused by a particular pest could also be retrieved using a similar method.

To retrieve the related images, the search is done in two steps. The first step matches the images by comparing the standard deviations for the three colour components. In the

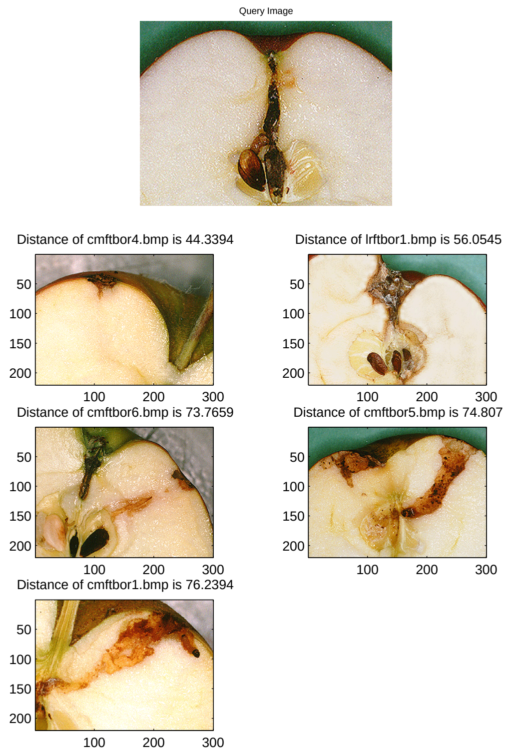


Figure 4: Query image and retrieved images of codling moth boring damage

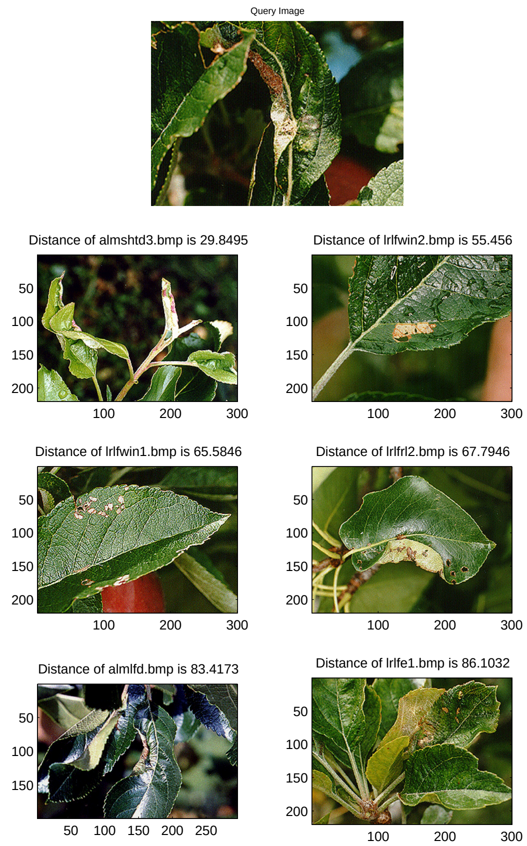


Figure 5: Query image and retrieved images of leafroller damage

second step, a weighted version of the Euclidean distance between the feature coefficients of an image selected in the first step and those of the querying image is calculated and the images with the smallest distances are selected and sorted as matching images to the query.

The algorithm described in these papers was then developed in MATLAB using a combination of the Image Processing Toolbox [8] and The UVI 300 Wavelet Toolbox [7]. The top of Figure 4 shows the query image while the bottom Figure 4 shows the retrieved images in the database. Each image displayed has the Euclidean distance from the query image displayed above it. As a second example Figure 4 shows a second query submitted to the database on codling moth boring damage and the resulting retrieved images while Figure 5 shows the results of a leafroller damage query.

2.1.Results

It appears that this technique is quite successful in retrieving images of a similar nature however adjustment of the parameters of the algorithm is required as more images are added to the repository. This could be the method by which candidate images are chosen which are then used as input to the next stage of the decision process. Each image already stored in the database will have the knowledge/rules associated with it to be passed to the inference engine.

In addition, there is also one obvious advantage of using this technique. Images taken by the orchardist could also be added to the database when they have been correctly identified. This would then enlarge the range of images available to be compared possibly improving the accuracy of the retrieval algorithm.

3.A Neural Network Classifier using Wavelets

Although the approach taken by [9] and [10] for comparing the images worked quit well, there were some instances where the algorithm failed. For example, in the retrieved images in Figure 5 contain two images of appleleaf curling midge damage (almshtd3.bmp and almlfd.bmp) instead of leafroller damage. This is because the Euclidean distance measure does not take into account the subtle differences between the different types of damage, especially when it comes to the problem of differentiating between appleleaf curling midge damage and leafroller damage.

To account for these subtle differences we chose to use a neural network [3] for the task instead because of its ability to learn effectively the important features of the data it is supposed to model and to generalise well on data that it has not seen before.

The objective of this part of the research was twofold: One, to see if a neural network could classify the pest by the damage to the fruit, and two, to see if this method was better than the approach taken by [9] and [10].

Structure of the dataset

The dataset comprised of 90 images of damage to apples caused by codling moth, appleleaf curling midge, and leafroller. The images were then processed using the technique described in [9] and [10]. The algorithm described in the papers was then developed in MATLAB using a combination of the Image Processing Toolbox [8] and The UVI.300 Wavelet Toolbox [7]. For each component in the RGB colour-space, a 16x16 feature vector is produced resulting in a 16x16x3=768 dimensional feature vector that describes the semantics of the image. We then used this 768 dimensional feature vector as the input to the neural network.

Architecture of the Neural Network

The entire classification system was comprised of 5 Neural Networks (NN) to reflect the five different types of damage that could be expected:

NN-alm-l	To classify appleleaf curling midge leaf damage.
NN-alm-f	To classify appleleaf curling midge fruit damage.
NN-cm	To classify colding moth damage.
NN-lr-l	To classify leafroller leaf damage.
NN-lr-f	To classify leafroller fruit damage.

Each NN was a Multi Layer Perceptron (MLP) [6] with 768 inputs, a hidden layer of 25 nodes, and 1 output node. 67 images were used as the training data-set broken down into:

10	Images of appleleaf curling midge leaf damage.
4	Images of appleleaf curling midge fruit damage.
22	Images of codling moth damage.
11	Images of leafroller leaf damage.
20	images of leafroller fruit damage.

23 images were used to test the classification system. The Scaled Conjugate Gradient Algorithm [4] was used to train the network; a variation on the standard backpropagation learning rule [5] reduce the time required to train the network due the the size of the input vector.

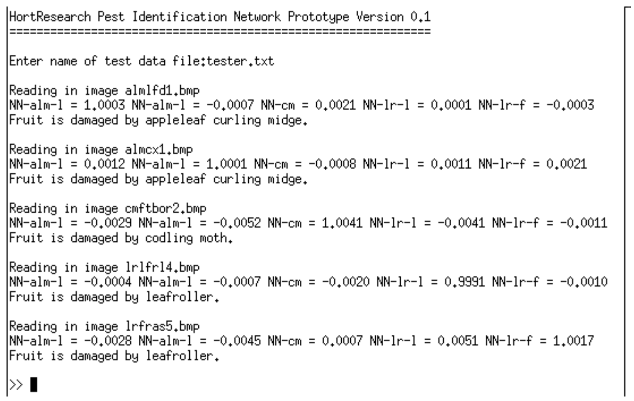
(a) almlfdl (b) almcx1 (c) cmftbor2 (d) lrlfrl4 (e) lrfras5

Figure 6: Subset of images used to test the classification system

Each NN in the classification system was trained with all 67 images and the output value for the output node changed depending on what each network was required to learn. For example the NN-alm-l was trained to give a 1 for any image that had appleleaf curling midge leaf damage and 0 for all the rest of the images.

3.1.Results

After presenting the 67 images to each NN in the classification system 200 times, the classification system was then tested set of 23 test images. There was a 95% recognition rate on images that the classification system had not seen before. Figure 6 shows an image of each type of damage from the test set. It correctly classified all five images into their respective damage categories. Figure 7 shows a screen-shot of the Matlab system in operation. To classify an image takes less than 1 second.



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HortResearch Pest Identification Network Prototype Version 0.1
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Enter name of test data file:tester.txt

Reading in image almlfd1.bmp
NN-alm-l = 1.0003 NN-alm-l = -0.0007 NN-cm = 0.0021 NN-lr-l = 0.0001 NN-lr-f = -0.0003
Fruit is damaged by appleleaf curling midge.

Reading in image almcx1.bmp
NN-alm-l = 0.0012 NN-alm-l = 1.0001 NN-cm = -0.0008 NN-lr-l = 0.0011 NN-lr-f = 0.0021
Fruit is damaged by appleleaf curling midge.

Reading in image cmftbor2.bmp
NN-alm-l = -0.0029 NN-alm-l = -0.0052 NN-cm = 1.0041 NN-lr-l = -0.0041 NN-lr-f = -0.0011
Fruit is damaged by codling moth.

Reading in image lrlfrl4.bmp
NN-alm-l = -0.0004 NN-alm-l = -0.0007 NN-cm = -0.0020 NN-lr-l = 0.9991 NN-lr-f = -0.0010
Fruit is damaged by leafroller.

Reading in image lrfras5.bmp
NN-alm-l = -0.0028 NN-alm-l = -0.0045 NN-cm = 0.0007 NN-lr-l = 0.0051 NN-lr-f = 1.0017
Fruit is damaged by leafroller.

>>
```

Figure 7: Resulting output in MATLAB

4.Conclusion and Future Work

This paper has detailed the image processing, and neural network classification methods applied to the task of identifying the pest that caused the damage to apple fruits and leaves in orchards.

Even at this stage in the research it can be seen that the feasibility of using these techniques is quite encouraging. Given the high classification rate on a standard neural network without any special alteration to the learning algorithm, or any other complementary information about the nature of the images, it can be seen that this direction should provide even more fruitful results.

The next step is to expand the image data base and expand the system to include other information about the damage that can be input by the orchardist with the aim of increasing the accuracy classification system. There has already been some preliminary research into integrating both audio and visual information to the problem of person identification, [2] and this could also be applied to the problem of pest identification as well.

We propose using rules in the form of text instead of audio input via Matlab's Fuzzy Logic Toolbox as shown in Figure 9 These rules could form the basis of the rules node in a Fuzzy Neural Network (FuNN) [3] which would then adapt these rules depending on the nature of the images being presented to the FuNN. This would give us a clearer idea about what information is important in order to classify each pest.

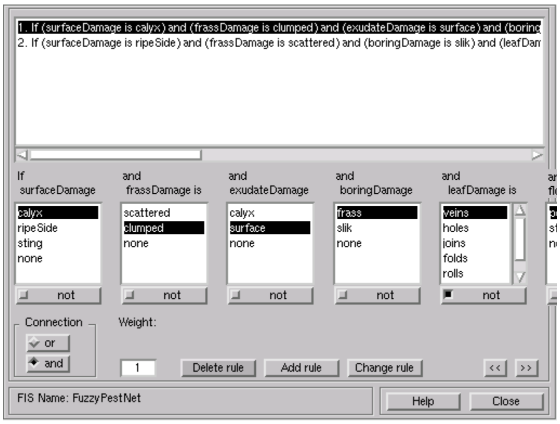

Figure 8: Rules for integration into the Pest Identification System

Once this has been completed, the overall system can be designed. Our current idea for the pest identification system is that it be an expert system that takes both image inputs and input from a keyboard. The image would then be pre-processed using the wavelet-analysis technique and the combination of the wavelet-data and text passed onto a collection of FuNN networks where one or more FuNNs model the damage caused by a particular pest. The architecture of the system would look something like the one presented in Figure 9.

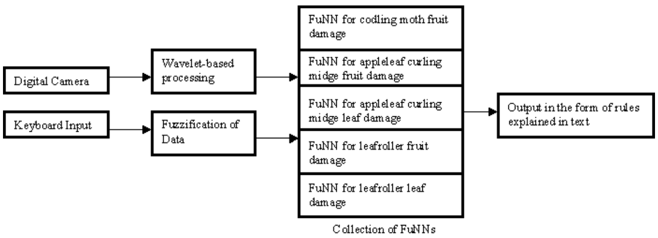

Figure 9: Overall architecture of the HortResearch Pest Identification System

Acknowledgement

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