Imaged Based Species Recognition System

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Abstract— **Animal species recognition is one area in which a limited amount of research has been undertaken. Especially in the pest control domain, basic primitive technologies are still used, such as identifying species in a tracking tunnel by capturing ink footprints on paper. These traps only differentiate various species by varying the baits used in the trap. This is not a reliable method.**

The main aim of this research is to develop a species recognition system for traps. This system uses an eigenface based identification technique. This imaged based sensing application is focused on feral rodents such as possums, cats and weasels.

Traditionally, the eigenface technique is used in the human face recognition domain. This technique is novel in animal species recognition domain. When the technique was applied to animal images with different backgrounds, it had 55%, 33% and 45% successful detection rates for possums, cats and weasels respectively. Once the background is removed from the training images the detection rate increased significantly to 65%, 52% and 64% respectively.

Keywords: Eigenfaces; Animal Species Recognition; Wildlife Monitoring.

I. INTRODUCTION

The New Zealand government has invested 4 million dollars to introduce and carry out extensive research on self-resetting trap technologies to control animal pests [1]. A problem with current technologies is that they do not identify the species before they activate the killing mechanism. Therefore they could kill any species that goes into the trap.

At present the New Zealand Department of Conservation spends about $20 million dollars a year controlling possums and ground based pests like rats and stoats [2]. This money is mostly spent on traditional traps and maintenance. At present there is significant public opposition to other pest control practices such as 1080 poison drops.

Animal species recognition is one of the areas in which a limited amount of research has been undertaken. Especially in the pest control domain, basic primitive technologies are still used. An example is identifying species in a tracking tunnel by capturing ink footprints on paper [3]. This method is currently used to identify, understand and study the animal species in a given area (refer to Figure 1). If pests are identified in a given area, then pest control traps can be placed in the area. A problem with this approach is that these traps cannot distinguish pest species from other species in a reliable way. The only way they differentiate between species is by varying the baits used in the traps. However this is not a reliable method.

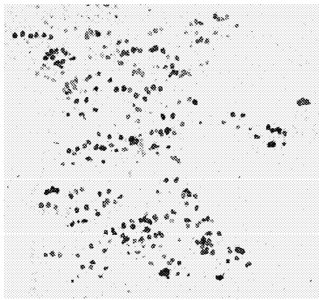

Figure 1: Mouse Footprints [3]

II. CURRENT IDENTIFYING METHODS

A. *Identify Species by Footprints*

In this method, animals entering the trap firstly walk through an ink well and then walk on white paper. This method records the footprint information onto the white paper (refer to Figure 2). Then this paper can be used to analyse the footprint information. There have been a number of published research reports that correlate the footprint information with actual species [4-7].

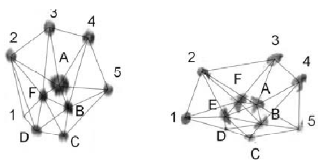

Figure 2: Measured Footprints [5]

Often this method requires trained experts to identify the animal species. This method also requires human effort to collect footprint samples and replace the ink and paper.

B. *Identify Species by Image Processing Techniques*

There are some research publications in the animal species recognition domain that have reported using image processing techniques. All of these researches have been carried out on larger animals, where species identification is easier. The larger animal species usually have unique skin features, sizes or shapes which can be used to identify them. These image processing based methods are rapidly developing due to improved and cheaper camera technologies and smart-phone based video applications [8].

Most of those projects were conducted on large animals such as tigers, lions, giraffes, etc.

Ramanan, Forsyth and Barnard identified larger animals from video footage [9]. They have divided the target animal image into a number of pictorial representations using rectangle structures. The configuration and orientation of these rectangles can be used to identify the animal species (refer to Figure 3). Their research expanded into the area of animal texture detection. They have developed a library of animal textures. By incorporating texture detection and pictorial representation, the accuracy of the system can be improved [9, 10].

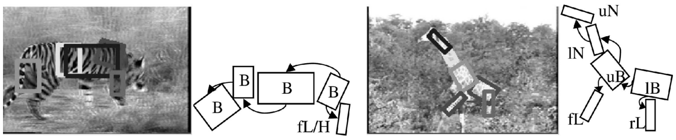

Figure 3: Pictorial Representation of Animals

III. Eigenface Technique

The eigenface technique is normally used in human face recognition. In a typical application, a training set is created with different human faces that need to be identified by the system. The mean of the input face images is calculated, and then mean is subtracted from the training set images to obtain a mean-shifted training set. This is known as normalizing the training set. For the mean-shifted training set images, the eigenvectors with the largest eigenvalues are calculated. These are known as the principle components. These principle components keep most of the facial features. Finally the eigenface technique projects the mean-shifted images into the eigenspace, using the principal eigenvectors, those eigenvectors with the largest eigenvalues [6, 11, 12].

In this application eigenvectors are used to distinguish between cats, possums and weasels.

The eigenface algorithm can be broken down into few steps [6, 11, 13].

Step 1: Obtain an animal face training set $I_1, I_2, \ldots\ldots, I_M$

Step 2: Convert each image I_i into a vector Γ_i (Convert the NxN image into an N^2x1 vector)

Step 3: Calculate the average animal face vector Ψ:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i$$

Step 4: Subtract the average face vector from Γ_i to get Φ_i:

$$\Phi_i = \Gamma_i - \Psi$$

Step 5: Calculate the covariance matrix C of these vectors:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \text{ } (N^2 x N^2 \text{ matrix})$$

where $A = [\Phi_1 \Phi_2 \ldots \Phi_M]$ (N^2xM matrix)

Step 6: For the matrix AA^T, calculate the M eigenvectors u_i with the largest eigenvalues [6].

Once the eigenvectors have been computed from the training set, unknown images can be fed into the system for species identification. Before input to the identification system, the input image needs to be normalized. This process can be split into four steps for a given unknown image Γ [14, 15].

Step 1: Calculate $\Phi = \Gamma - \Psi$

Step 2: Calculate $\hat{\Phi} = \sum_{i=1}^{M} w_i u_i \quad (w_i = u_i^T \Phi)$

Step 3: Calculate Euclidean distance $e_d = \|\Phi - \hat{\Phi}\|$ [6]

Step 4: If $e_d < T_d$ then Γ is a one of the animal species, where T_d is a preset threshold value

In a typical application, the Euclidean distance is calculated. Then this distance is compared against a known threshold value. If the Euclidean value is less than the threshold, the input unknown image is one of the training set images. Otherwise it is not.

IV. EIGENFACES FOR SPECIES INDENTIFICATION

The basic process of eigenfaces can be described as flowchart below (refer to Figure 4 below).

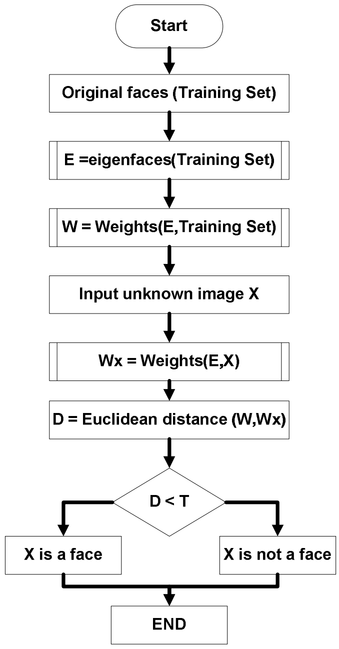

Figure 4: Eigenface Recognition Process

The first stage of the process is to obtain a training set of different animals. The training set is then normalized by subtracting the mean from the input animal faces to obtain mean-shifted images.

Figure 5: Normalized Training Set

The next stage is to calculate the eigenfaces for the training set data. This process is typically an intensive task to perform on a microprocessor. But this step does not need to run, during the recognition process. This step can be performed as part of initialization. Similarly calculating the training set eigenvectors and weights stage is part of the initialization process.

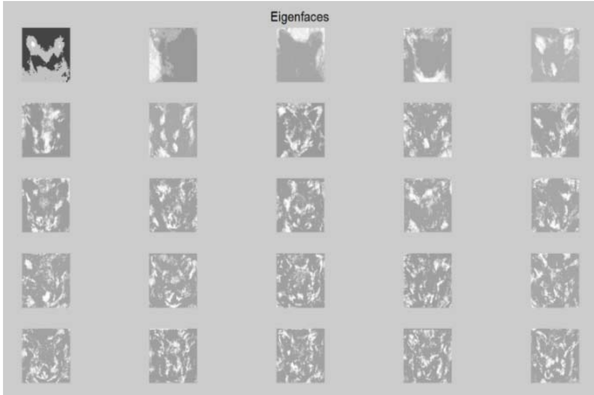

Figure 6: Computed Eigenfaces from training set

The next two steps are the processing of the unknown test image. The test image is normalized and the eigenvector weights for the input image are calculated. Finally these weights are used to generate a reconstructed face from the eigenvectors.

These steps take less processing power compared to the initialization. Therefore these steps can be performed reasonably quickly.

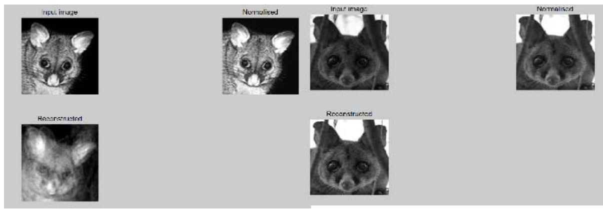

Figure 7: Reconstructed image

Finally the Euclidean distance is the measure of similarity between the reconstructed image and the normalized input image, to measure the difference between the two images. In this application there will be three different Euclidean distances for possums, cats and weasels. Then the lowest value out of three is selected as the animal species.

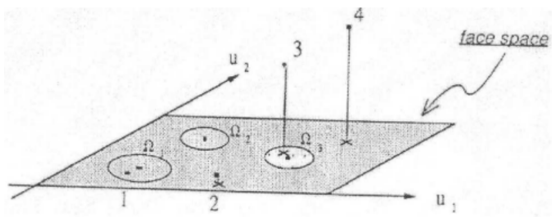

Figure 8: Euclidean Space

This recognition process is appropriate for an embedded system approach. Most of the processor intensive tasks are performed during the initialization stage. Once the initialization process is complete, the recognition process requires less processor resources. Therefore the recognition steps can be performed relatively quickly, in order to allow the trapping system to react quickly.

V. REFINEMENT

A problem with the eigenface technique is that it is designed to identify the images of the animals contained in the training set. For example, in the human recognition domain, the person in the image under test is expected to be in the training set. Under these circumstances the person in the image can be recognized with 75% accuracy [6, 13]. In this application, the system is attempting to identify the animal species rather than a particular individual animal. For example, the system is attempting to distinguish the species as cat, possum or weasel.

To overcome this problem, the training set was split into three groups: possums, cats and weasels. When the same species are grouped, the main facial features and shapes produce larger valued eigenvalues.

A second problem is that, within the same species, different animals can have quite different fur color variations. For example, there are two types of possum: black colored possums and lighter colored possums (refer to Figure 9 below).

Figure 9: Different colored possums

A third problem is that animals such as cats have different face shapes and different color patches on their fur. In this case it is difficult to obtain a suitable generic set of eigenvectors to apply to the input test images.

In all these cases, specific features tend to gain higher weightings on eigenvalues than the face shape and face features.

The last problem is the background of the image. Animal images with random backgrounds produce strong eigenvectors primarily related to the background information. These images further reduce the detection rate. Therefore all the training set images had been preprocessed. The background has been replaced with a uniform black color (refer Figure 10). Now all the eigenvalues have very strong correlation with the actual animal facial features rather than the background.

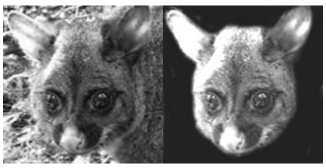

Figure 10: Possum Image before and after prepossessing

VI. RESULTS

The initial set of experiments were conducted with one large training set. All the animals were part of one training set. Also all the images had their own original background.

One training set with Background	
Animals	**Detection Rate**
Possums	55%
Cats	33%
Weasels	45%

Table 1: Animal Detection Rates

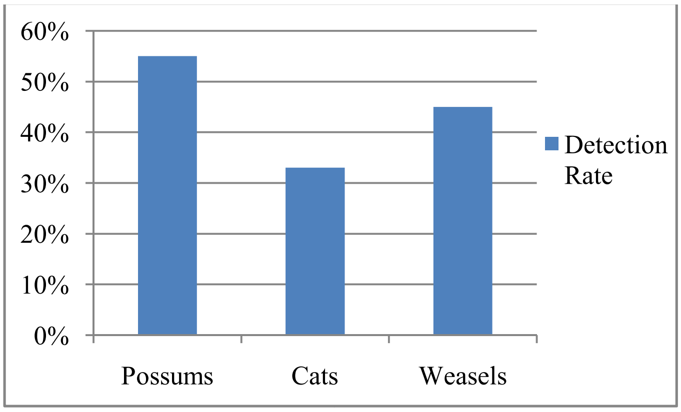

Figure 11: Animal Detection Rate

Possum detection has the highest accuracy. This is because the variations between different possums were smaller than for cats and weasels. On the other hand, the cat images had large variations, due to different facial fur patterns and colors. Hence cats had the lowest detection rate.

Even though weasels have different facial colors and patterns, their head size and main features (such as nose and ears) are distinctive.

Then the training set was split by species into three separate groups and the original background was removed from the training images. As a result, the system accuracy improved significantly.

Different Training sets without Background	
Animals	**Detection Rate**
Possums	65%
Cats	52%
Weasels	64%

Table 2:Animal Detection Rate

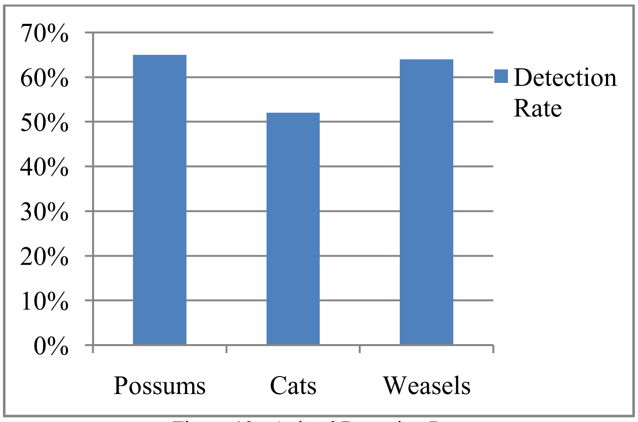

Figure 12: Animal Detection Rate

VII. CONCLUSION

The eigenface technique is novel in the animal species identification domain. When the technique was used in its original form, the identification rate was low. But with some preprocessing of the training set images, the accuracy of the system was improved significantly.

The main advantage of the eigenface based technique is that most of the computationally intensive tasks can be performed prior to detection time. During the detection time there is only a minimal number of computation steps to perform.

The proposed system will remove the requirement for specialized, trained experts to identify the animal species from their footprint pattern or fur samples. One drawback of the system is that the initial cost of the system is higher than for the conventional trap, but maintenance costs should be lower. Also in future, the system could be modified to monitor and study the animal population and animal behavior.

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