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Novel Embedded System Based Species Recognition System for Pest Control

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Abstract: To develop a species recognition system for a resettable trap using novel species identification techniques.
Classical pest control techniques are currently used to identify the pest population in New Zealand forests. The main interest of Department of Conservation (DOC) is to identify the pest before setting the traps and collect pest population information regarding certain types of pests. The main aim of this work is to design and develop a novel robust system which can be used to identify the animal in real time in different environmental conditions.
We propose an image recognition technique based system to identify the pest. To be specific, identifying pests by body features and fur patterns color, using image processing techniques. For the test system, a GumstixOvero Fire COM (computer-on-module) with a Texas Instruments OMAP embedded platform is used to run the image processing algorithms on a Windows based CE operating system.

Keywords: Backprojection, Eigenfaces, Edge Detection, Resettabel trap

1. Introduction

In recent times with new technologies, self-resettable traps have been introduced and trial runs have been carried out. Moreover the government had invested 4 million dollars to introduce and carry out extensive research on self-resetting trap technologies [1]. The down side of the current technology is; it does not identify the species before it activates the killing mechanism. Therefore, this could kill any species which goes through the trap.

At present DOC 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 huge public opposition to current pest control practices like 1080 poison drops.

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 in use. An example is identifying species on a tracking tunnel using ink paper [3]. This method is currently used to identify, understand and study the species in a given area (refer to Figure 1). Once, the Department of Conservation (DOC) gains knowledge of the pest population in a given area, pest control traps can be placed in the area to control the population. The only down side of this approach is that these traps do not have an inbuilt intelligence to distinguish the pest from other species. The only way they try to avoid killing the wrong animal is by using an appropriate bait. However, this is not a reliable method.

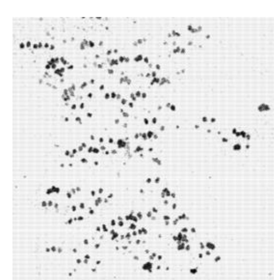

Figure 1. Mouse Footprints [3]

2. Current Technologies

Currently there are two main ways to detect animals, they are artificial intelligence based and image processing techniques based identification. The oldest technology is the use of an ink paper tunnel to identify the foot prints.

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A. Artificial Intelligence Based Identification

Most AI based techniques are purely used in computer based systems. These systems naturally require intensive computational computing power. Also required large number of training images.

One of the techniques used for human recognition is the pictorial structures technique [4]. A pictorial structure model for an object is given by a collection of parts with connections between certain parts. This structure gives a basic appearance of the image, which can be used with neural network algorithms [4].

P. Felzenszwalb and D Huuenlocher incorporated pictorial structural representation alone with face recognition techniques to improve the accuracy of the neural network system to identify humans. Their system can be used identify a human more accurately and also can guess the sex of the person [4].

Hence this system is going to be used in outdoor environment, power hungry systems are not suitable. The second problem is; it is difficult to obtain large number of training images of possums to train the system.

B. Image Processing Techniques Based Identification

Image processing techniques based identification, is more suitable for smaller embedded microprocessor based systems. These systems are inheritably limited resources, such as system memory and computational power. Therefore, these systems are less power hungry and smaller in physical size. Therefore, this type of systems are ideal for this application.

The image processing technique based technology is rapidly improving due new camera technologies and smart-phone based video applications [5, 6]. The OpenCV development source image processing tool box plays a major part of in this area. OpenCV started in the mid-1990s and now it contains more than 2500 image processing algorithms. This image processing toolbox has been widely adopted by major global companies like Google, Yahoo, Microsoft, Intel, IBM, Sony, Honda and Toyota. This toolbox is compatible with all major operating systems [7].

Stochastic AND-OR template (Deformable templates and compositional hierarchy) are widely used in computer vision for object modelling [8, 9]. In this method, pre-learned animal data is stored in a database. Z. Si and S. Zhu have saved several features such as a sketch of the animal face, the fur direction of the animal and flatness of the face. Then animal face information is fed through an AND-OR template for identification [8].

Gavrila and Philomin[10] developed a real time object detection system for vehicles using a template hierarchy stochastic optimization technique [10]. The other speed optimizing technique is removal of the background image. Then all the computational power can be used for the region of interest of the image. To identify the region of interest, an integral image technique was used [11]. The integral image technique is primitive when compared with steerable filters [12], but this technique required modest computational power. Also it can be used to identify the human faces.

Object recognition by edge detection is one of the commonly used methods [13-15]. After edge detection, there are many other techniques that can be used to extract information. A. F. Felzenszwalb used edge detection to extract information and then used Hausdorff distance as a simple shape comparison measure to identify people [10, 14, 16].

The example based object detection [17-20] method, is used to identify the different features of an object individually. As an example, the human body is separated into head, left arm / leg and right arm / leg. Then each feature is identified separately and overall the system identifies the human as whole. This method can be used to detect any object, given that the object contains some distinct features which can be used as the example base.

Matching shapes image processing approach can be used to identify the similarity between objects [21]. This technique will be useful in the species recognition domain. Most of the target species have similar features. Therefore, this technique can be used to categorize different animal species. As an example there are several different rat species, under the rat category, so this technique can be used to differentiate each rat species. There are two approaches to the shape matching technique. They are feature-based and brightness-based techniques. The feature-based approach involves the use of spatial arrangements of extracted features such as edges or junctions [21, 22]. The brightness-based technique uses the brightness value of pixels [21, 23].

W. T Freeman and M. Roth used an orientation histogram technique to detect hand gestures [24, 25]. This technique can be used to identify the animal orientation by converting the data into a histogram. Each gesture consists of its unique vector histogram and this unique histogram can be used to identify the gesture. The histogram data is stored into a database and then the test image is compared with the database [24].

For skin color detection, histogram learning techniques are widely used [26]. According to Jones and Rehg[26] this statistical approach can be a more powerful cue for detecting people in unconstrained imagery. I have conducted extensive investigation on skin color detection algorithms applied to animal fur color detection (please refer to section 4.0).

From the literature survey, it has been found that neural network image processing systems have the added complexity of data mining. These systems are hard to implement on embedded based platforms. Therefore, the research will be focused on an embedded platform with combination of image processing techniques to identify wild rodents (small animals).

3. Investigations and Feasibility with Image Processing Techniques

Preliminary investigations and experiments have been conducted on edge detection and back projection techniques. It has been found that basic possum identification can be achieved by using edge detection and back projection. Initial simulation was carried out using MATLAB, and then both algorithms were implemented in C language and trialed on a Gumstix ARM embedded platform.

A. Edge Detection

Edges within an image correspond to intensity discontinuities that result from different surface reflectance of objects, various illumination conditions, or varying distance and orientations of objects from a viewer [27]. Edge detection is one of the important and fundamental methods in image analysis and computer vision. An object can be identified by its shape, texture and color. The shape of an object is one of the important properties, that can be realized from its edges. If an image processing program can find the edges which enclose an object, then it can obtain important features like size and shape about that particular object. A variety of edge detectors have been proposed, including classical methods such as the Prewitt and Sobel operators, as well as the more sophisticated algorithms like Canny [28].

Common steps for edge detection usually are using orthogonal gradient operator, directional differential operator and some other operators relevant to second-order differential operator. Sobel operator is a kind of orthogonal gradient operator [29]. For a continuous function f(x, y), in the position (x, y), its gradient can be expressed as a vector (the two components are two first derivatives which are along the X and Y direction respectively).

The concept of edge detection can be simply described as follow: a digital image consists of many pixels organized in rows (x direction) and columns (y direction); in most of the case, a pixel (except those pixels on the edges of an image) will have eight adjacent neighboring pixels. By comparing the intensity level of a pixel with its adjacent pixels, the significant difference in the intensity level between adjacent pixels suggests that particular pixel is likely to be on the edge.

$$\nabla f(x,y) = \begin{bmatrix} \dfrac{df}{dx} \\ \dfrac{df}{dy} \end{bmatrix} \tag{3.1}$$

$$\nabla^2 f(x,y) = \frac{d^2 f(x,y)}{dx^2} + \frac{d^2 f(x,y)}{dy^2} \tag{3.2}$$

$$\frac{d^2 f(x,y)}{dx^2} = f(x+1,y) + f(x-1,y) - 2f(x,y) \tag{3.3}$$

$$\frac{d^2 f(x,y)}{dy^2} = f(x,y+1) + f(x,y-1) - 2f(x,y) \tag{3.4}$$

(x-1, y-1)	(x-1, y)	(x-1, y+1)
(x, y-1)	(x, y)	(x, y+1)
(x-1, y-1)	(x+1, y)	(x+1,y+1)

Figure 2.A pixel and its' 8 adjacent pixels

In terms of implementation, the image pixel matrix is convoluted with a 3 x 3 mask. The result indicates intensity level change of each pixel related to its adjacent pixels. The mask can be filled with different values depending on the methods used. Commonly used methods are Sobel, Prewit Kirsh masks. After convolution, a threshold is applied to keep only meaningful edges. The following example shows the use of sobel masks for detecting the edges [30].

-1	0	1
-2	0	2
-1	0	1

1	2	1
0	0	0
-1	-2	-1

Figure 3. Sobel Masks for edge detection

Figure 4. (a) Original image of a Possum (b) Sobel edge detection result

B. Histogram Back Projection

The back projection method is a way of recording how well the pixels of a given image (test image) fit the distribution of pixels in a histogram model (from a model image). The method was introduced initially by Swain and Ballard and then developed in research projects at Columbia University. In the content-based visual retrieval domain for detecting color regions, it was chosen the color set back-projection algorithm. This technique provides the automated extraction of regions and the representation of their color content [31]. The histogram back projection algorithm can be divided into four steps.

- Transform from the RGB color space to HSV color space.
- Create histogram thresholds based on a model image
- Plot a histogram of the testing image
- The extraction of the region features based on the threshold model

RGB color is converted to HSV as follow:

$$M = \max(R, G, B) \tag{3.5}$$

$$m = \min(R, G, B) \tag{3.6}$$

$$C = M - m \text{ (known as the Chroma)} \tag{3.7}$$

And then

$$H' = \text{undefined} \quad \text{if } C = 0 \ (R = G = B) \tag{3.8}$$

$$H' = (G - B)/C \quad \text{if } M = R \text{ (R is maximum) and } G \geqslant B \tag{3.9}$$

$$H' = (G - B)/C + 6 \quad \text{if } M = R \text{ (R is maximum) and } G < B \tag{3.10}$$

$$H' = (B - R)/C + 2 \quad \text{if } M = G \text{ (G is maximum)} \tag{3.11}$$

$$H' = (R - G)/C + 4 \quad \text{if } M = B \text{ (B is maximum)} \tag{3.12}$$

Then H = 60 * H'. When C equals zero, we typically assign H to zero as well.

Also

$$V = M \tag{3.13}$$

$$S = C / V \tag{3.14}$$

After converting all the pixels from RGB format to the HSV format, we need to plot a histogram of the hue H based on a model image. The next few steps of the back projection are explained using the following example.

If we need to look for an animal with brown color such as a possum, we obtain an image with only the color of the animal fur. Then convert all the pixels of this model image (image of possum fur) to HSV values and plot the histogram of Hue, Saturation and Value. By observing those histograms, we can see most of the Hue values are concentrated within a very narrow band on the Hue spectrum. This spectrum defines the upper and lower thresholds of hue for possum fur color (refer to Figure 5 and Figure 6 below).

Figure 5. An image of a possum's fur

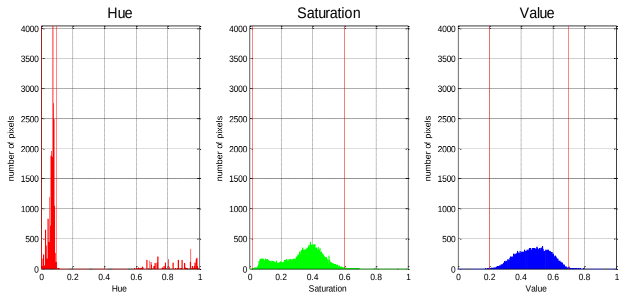

Figure 6. Hue, Saturation and Value histogram of a Possum fur image

If we want to find any possum fur color region within a test image, (for example, a picture of a Brushtail possum) this technique can be applied.

Figure 7. A common Brushtail Possum

Convert all pixels of test image into HSV format and plot the histogram of Hue, Saturation and Value as follow:

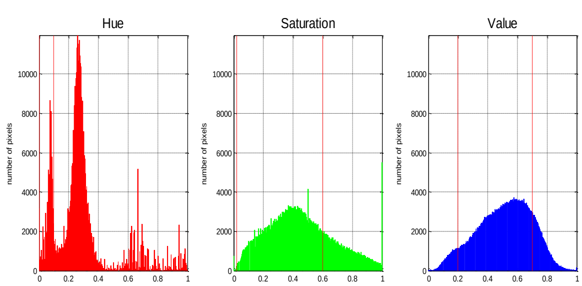

Figure 8. Hue, Saturation and Value histogram of the Brush tail Possum image

Use the thresholds we derived from the possum fur image, for the pixels of the test image. Pixels outside the range thresholds are marked as 0, and all other pixels between the upper and lower thresholds are marked as 1. Then we obtain a mask image for possum color from the test image (refer to Figure 9 below).

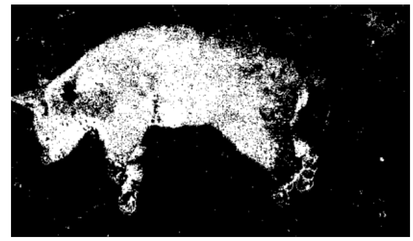

Figure 9. Mask for Possum fur color

Finally, apply this mask to the original test image and we obtain a picture with only the possum fur color range remaining. There is some noise on the mask image (small regions with color close to possum fur color but not part of possum).

Figure 10. Use the fur color mask to find possum from image

Erosion is one of the fundamental operations in morphological image processing. Erosion is often used after back projection operations to reduce the noise. A pixel will be set to 0 if any of the neighboring 8 pixels is 0. The area of interest will shrink after applying erosion. Those small areas with only few pixels which are usually noise, shrink to zero.

Dilation is often used after erosion operation. It is another basic operation in mathematical morphology, developed for binary images. The dilation operation usually uses a structuring element for probing and expanding the shapes contained in the input image. Dilation grows the area of interest. It sets the pixel in the masking image to 255 if it or any of the neighboring 8 pixels is 255. When applying dilation after erosion, the area of interest will be smoothed on the edges.

4. IMPLEMENTATION

This novel approach is specially designed to measure the length and color of an animal. Using this approach birds and pests like possums can be distinguished easily.

Figure 11. Trap Setups

Figure 11 above shows the setup of the fully automated trap. This unit consist of Gumstix Overo Fire COM (computer-on-module) with a TI OMAP3530 ARM processor on board and e-CAM21 USB camera for image capture. The system is run on windows CE 1.0 operating system.

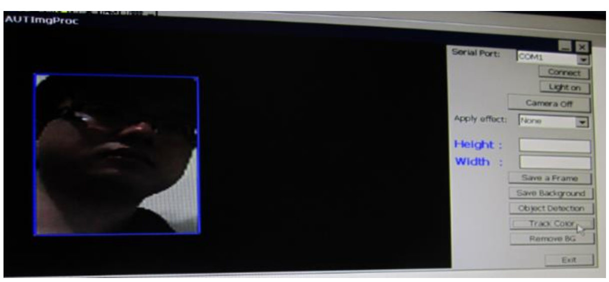

Figure 12. System Color tracking

This novel system utilizes back projection and edge detection to measure length and height of an animal. This information can be used to identify the animal.

As the animal walk pass the tunnel its length and height will be recorded. Then this information is used to identify the animal.

Typically possums head and body length vary from 32-58 cm with a tail length of 24-40 cm [32]. Therefore, total length of a possum is 56-98 cm. Typically, largest Kiwi bird's species have standing height of 45cm. But their length is lot less than possum total length. Moreover, possums are lot shorter that a Kiwi bird.

5. Conclusion

Image processing techniques such as edge detection, back projection and noise removal methods are used. The edge detection uses the first and second derivatives to find the intensity discontinuities that result from different surface reflectance of objects. Back projection method transforms pixels of a model image, into HSV (Hue, Saturation and Value) format to obtain the thresholds from the histogram. Then based on the thresholds from model image to extract regions of features from incoming images.

At the end, our system can identify animals by their size and color. However, only based on color and size to identify animals is not reliable enough.

Therefore, in future more sophisticated techniques like Eigenfaces and Fisherfaces techniques need be to investigated to improve the accuracy of the system.

References

[1] ONENews. (2010). *Self-resetting pest traps hope to save money*. Available: http://tvnz.co.nz/politics-news/self-resetting-pest-traps-hoped-save-money-3840058/video

[2] K. Wilkinson. (2010). *$4m invested in self-resetting trap pilot project*. Available: http://www.scoop.co.nz/stories/PA1010/S00294/4m-invested-in-self-resetting-trap-pilot-project.htm

[3] D. W. Craig Gillies, "A short guide for identifying footprints on tracking tunnel papers," vol. OLDDM-63018 1

[4] P. Felzenszwalb and D. Huttenlocher, "Pictorial Structures for Object Recognition," *International Journal of Computer Vision*, vol. 61, pp. 55-79, 2005/01/01 2005.

[5] Gray Bradski and A. Kaehler, *Learning OpenCv*. Sebastopol: O' Reilly Media Inc, 2008.

[6] S. M. Umer, A. A. Chandio, M. W. Khan, T. Zahid, and F. Muhammad, "A Study of Distinctive Localization and Navigation Methods for Mobile Robots," *Int. J. Com. Dig. Sys*, vol. 4, 2015.

[7] OpenCV. (2012, 18/11/2012). *OpenCV*. Available: http://opencv.org/

[8] S. Zhangzhang and Z. Song-Chun, "Unsupervised learning of stochastic AND-OR templates for object modeling," in *Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*, 2011, pp. 648-655.

[9] S.-C. Zhu and D. Mumford, "A Stochastic Grammar of Images," *Foundations and Trends in Computer Graphics and Vision*, vol. 2, pp. 259-362, 2006.

[10] D. M. Gavrila and V. Philomin, "Real-time object detection for vehicles," in *Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on*, 1999, pp. 87-93 vol.1.

[11] Y. Freund and R. E. Schapire, "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting," *Journal of Computer and System Sciences*, vol. 55, pp. 119-139, 1997.

[12] W. T. Freeman and E. H. Adelson, "The design and use of steerable filters," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 13, pp. 891-906, 1991.

[13] J. Canny, "A Computational Approach to Edge Detection," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. PAMI-8, pp. 679-698, 1986.

[14] P. F. Felzenszwalb, "Learning models for object recognition," in *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, 2001, pp. I-1056-I-1062 vol.1.

[15] S. Rashid, "Computerized Exudate Detection in Fundus Images Using Statistical Feature based Fuzzy C-mean Clustering," *International Journal of Computing and digital systems*, vol. 2, pp. 135-145, 2013.

[16] W. Rucklidge, *Efficient Visual Recognition Using the Hausdorff Distance*: Springer Berlin Heidelberg, 1996.

[17] A. Mohan, C. Papageorgiou, and T. Poggio, "Example-based object detection in images by components," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 23, pp. 349-361, 2001.

[18] K. K. Sung and T. Poggio, "Example-based learning for view-based human face detection," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 20, pp. 39-51, 1998.

[19] F. A. Albalooshi, "Hyperspectral Image Segmentation by Self Organized Learning-Based Active Contour Model," *Int. J. Com. Dig. Sys*, vol. 5, 2016.

[20] M. Ghazal, Y. Alkhalil, S. S. Ali, F. Haneefa, and E. Rashed, "Archival and Retrieval of Lost Objects using Multi-feature Image Matching in Mobile Applications," *Int. J. Com. Dig. Sys*, vol. 5, 2016.

[21] S. Belongie, J. Malik, and J. Puzicha, "Matching shapes," in *Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on*, 2001, pp. 454-461 vol.1.

[22] Y. Gdalyahu and D. Weinshall, "Flexible syntactic matching of curves and its application to automatic hierarchical classification of silhouettes," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 21, pp. 1312-1328, 1999.

[23] B. Moghaddam, C. Nastar, and A. Pentland, "Bayesian face recognition using deformable intensity surfaces," in *Computer Vision and Pattern Recognition, 1996. Proceedings CVPR '96, 1996 IEEE Computer Society Conference on*, 1996, pp. 638-645.

[24] F. W.T. and R. Michal, "Orientation Histograms for Hand Gesture Recognition," presented at the IEEE Intl. Wkshp. on Automatic Face and Gesture Recognition, Zurich, 1994.

[25] R. K. McConnell, "Method of and apparatus for pattern recognition," U. S. Patent No. 4,567,610 Patent, Jan. 1986.

[26] M. J. Jones and J. M. Rehg, "Statistical color models with application to skin detection," in *Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on.*, 1999, p. 280 Vol. 1.

[27] P. Fieguth, "Image Processing," in *Statistical Image Processing and Multidimensional Modeling*, ed: Springer New York, 2011, pp. 423-432.

[28] J. I. Siddique and K. E. Barner, "Wavelet-based multiresolution edge detection utilizing gray level edge maps," in *Image Processing, 1998. ICIP 98. Proceedings. 1998 International Conference on*, 1998, pp. 550-554 vol.2.

[29] G. Wenshuo, Z. Xiaoguang, Y. Lei, and L. Huizhong, "An improved Sobel edge detection," in *Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on*, 2010, pp. 67-71.

[30] L. Jiang, W. Zhou, and Y. Wang, "Study on improved algorithm for image edge detection," in *Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference on*, 2010, pp. 476-479.

[31] L. Stanescu, D. D. Burdescu, and A. Ion, "Using the color set back-projection algorithm in retrieval and evaluation of endoscopic images from patients with peptic ulcer," in *Information Technology: Research and Education, 2006. ITRE '06. International Conference on*, 2006, pp. 126-130.

[32] L. Cronin, *Cronin's Key Guide to Australian Mammals*. Sydney: Allen & Unwin, January 2008.

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