Paper:

Neural Network Vision-Guided Mobile Robot for Retrieving Driving-Range Golf Balls

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We developed an autonomous mobile robot with neural network (NN) vision that searches for and collects golf balls on an open or an indoor golf driving range. The robot recognizes range borderlines by red stripes. Scattered golf balls are collected using mechanically designed rotating blades. The NN vision identifies objects that are not golf balls and prevents the robot from picking them. The vision system is robust enough to navigate an open field and pick up the golf balls any time of day. Results of the experiments showed that our proposal operates accurately and reliably.

Keywords: neural network vision, autonomous mobile robot, driving-range golf ball retrieval robot

1. Introduction

Biological research on how the brain works has inspired the design of Artificial Neural Networks ANNs [1–3]. The brain's capabilities in processing information and making instantaneous decisions in complex, and uncertain environments has attracted the attention of many researchers studying and attempting to mimic its computational abilities. The huge number of connections linking neurons in parallel enables human beings to learn. Motivated by this very efficient computational biological model scientists have attempted to build computing systems called artificial neural networks (ANN), that process information similarly [4], mimicking the brain's architecture by linking together processing elements called artificial neurons. Variable strength connections, called connection weights, implement synapses, which enable learning and communication between processing elements. By changing these connecting weights, the network collectively produce solutions and successful behavior. The ANN has been used in such applications as in process monitoring and optimal control [5, 6], communication [7, 8], power [9, 10], robotics [11, 12], decision fusion and pattern recognition [13, 14].

We applied the ANN to vision for a robot that retrieves driving-range golf balls. The range is classified as alternative golf facilities, providing players a place to practice hitting golf balls. The large number of users means that golf balls tend to accumulate quickly, confusing golfers on where their balls landed. Accumulated golf balls are collected to prevent confusion and enable golf balls to be reused. Personnel attempt to collect balls during range use may be hit by high-impact balls, which is why the alternative of an autonomous mobile robot that retrieves golf balls when the range is in operation is attractive. The robot designed for this operation has built-in vision that detects and retrieves golf balls, and detects range boundaries indicated by red borders. A remote controller module in the robot interrupts autonomous operation, enabling the robot to be operated manually at remote locations. The robot's ball collector has 4 metallic blades set to prevent balls from jamming. These are connected to a cylindrical pipe at intervals of 90-degrees. The Blades sweep balls up the collector ramp, into the chute, and into the storage bins. The edge of the collector ramp is near but does not contact the ground, enabling blades to sweep balls up the ramp. The chute narrows down to a single-ball trough for ball counting. Results of experiments showed that the vision system successfully identified and retrieved balls on open and indoor fields and distinguished objects other than golf balls, preventing the robot from collecting such objects.

2. Robot Vision

For vision, the robot uses a webcam with a frame rate of 30 frames per second and compatible with USB 2.0 and 1.1 standards. Balls are assumed to be white. To identify objects, a 120×160 colored image is captured through the camera and converted to a binary image using thresholding. Each pixel is evaluated and white pixels are set to 1 and non-white pixels to 0. Eq.(1) detects white pixels [15]:

$$D = \sqrt{(255-R)^2 + (255-G)^2 + (255-B)^2} \quad . \quad (1)$$

where:
R : red pixel component
G : green pixel component
B : blue pixel component

If D is less than tolerance k, the pixel is identified as white and labeled 1. We tested different k and found that 20 gave the best result. From the binary image, adjacent pixels with a value of 1 are grouped together through an algorithm called labeling. Pixels that belong to one object have similar labels.

To remove unwanted objects in the image we conducted filtering, counting the number of pixels that belonging to an object. If the object has a pixel count within 20 to 121 it is retained and those outside this are filtered out. After filtering, the center or position of objects is obtained by averaging X and Y coordinates of pixels belonging to an object. Besides locating the object, the center of the object is used to get an 11×11 frame to be input into the neural network (NN). Note that a golf ball can fit in the 11×11 frame and its center is located at the center of the frame.

The NN is used to classify the object as a golf ball or other through its shape. The NN consists of an input layer with 121 nodes, a hidden layer with 80 nodes, and an output layer with a single node (**Fig.1**). NN output is 1 if it classifies the input as a golf ball and 0 if otherwise.

The following parameters are used to train the NN:
Error tolerance : 0.001
Learning parameter : 0.01
Momentum parameter : 0.001
Noise factor : 0.001
Maximum number of cycles : 240

Training data includes single golf balls, group of adjacent golf balls, and other unwanted objects. NN output ranges from 0 to 1. Any output greater than 0.8 is considered as a golf ball and if otherwise, not. Once the NN classifies an object as a golf ball, the X and Y coordinates or the object's location is obtained and passed to the control program. Those classified as non-golf balls are discarded.

To detect driving range boundaries and the starting point, RGB values of the image captured are converted to its corresponding HSI color space [15]. Using eqs.(2) and (3), Hue and Saturation components of the pixel are obtained [15]. The Hue component will describe which color the pixel belongs to, i.e. red, green, blue, etc. Saturation describes the degree to which the color is diluted with white. Red has high saturation while pink (red mixed with some white) has lower saturation. The intensity component gives the brightness of the color. Blue and red pixels have a corresponding binary image, both of which are labeled to filter out small red and blue objects, considered to be a noise when pixels number fewer than 20. The presence of red and blue in the image are also passed to the control program for robot action.

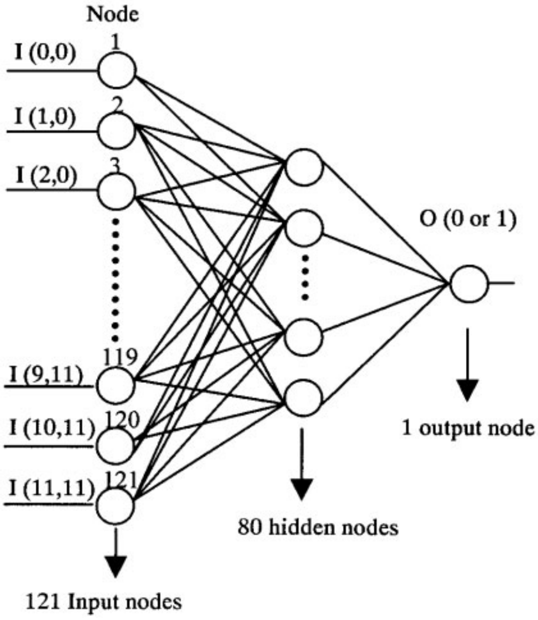

Fig. 1. Neural Network architecture for robot vision.

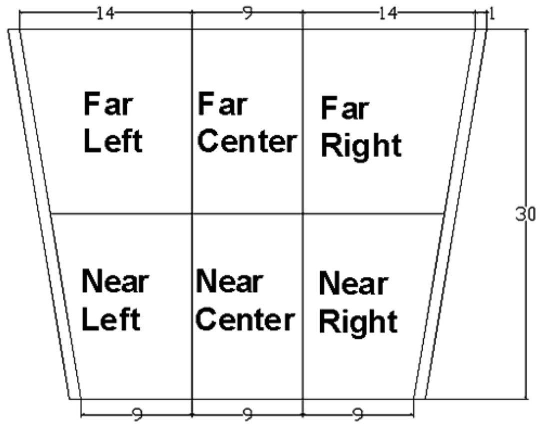

Fig. 2. Robot captured vision frame (in inches).

$$H = \cos^{-1}\left\{\frac{0.5[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{\frac{1}{2}}}\right\} \quad (2)$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] \quad . \ . \ . \ . \quad (3)$$

$$I = Intensity = \frac{(R+G+B)}{3} \quad . \ . \ . \ . \ . \ . \ . \ . \quad (4)$$