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Rushing out detection system for safe driving using foveated image processing

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Abstract

In this paper, we propose a detection system of dangerous situation for safe driving using foveated image processing and neural network (NN). This system detects the situation of a man rushing out that must be avoided while driving. A foveated image is transformed by Log Polar Mapping (LPM) [1, 2] from an image acquired from camera mounted on a car. LPM imitates primate visual system and it is possible not only to obtain both a high central resolution and a wide field view, but also to significantly reduce processing image data. This transformed image is suited for detection of an object that moves toward the camera. To detect this object, we calculate flow vectors on time-scaled images, and process them by NN that outputs a warning signal when a dangerous situaion is detected.

1 Introduction

A driving support system is a system that acquires informations of road and car environments by sensor(s) such as a camera or ultra sonic sensors on a car (inner type) or on road (outer type) and calls driver's attention to drive carefully by warning sounds or images when a dangerous situation is detected. There are some advantages of this system as follows [3]:

(1) Accident reduction in intersection.

(2) Reduction of driver's judgement load.

(3) Improvement of driver's awareness to safe driving.

As described above, there are two types of sensor mountings (inner and outer). We select inner type sensor mounting and, in our experiment, use an USB camera which is connected to a PC on a driving car to obtain informations in front of the car. The acquired images by the camera are transformed to LPM images which can not only to obtain high resolution in center and wide range, but also reduce data for processing[1, 2]. In this paper, we propose a detection system of dangerous situation for safe driving using foveated image processing and Neural Network (NN). We defined a dangerous situation which should be detected while driving is a man rushing out from left forward side of driver's car. We use optical flow method to extract motion in LPM images and apply them to NN to judge the scene. NN outputs a signal which notices dangerous situation. Finally we will show experimental results with actual road images. It will be compared with results of shrink images to show advantages of the LPM method.

2 Using methods

2.1 Log Polar Mapping

If we want to acquire broad visual informations, we use several cameras. However, this technique gets too large volume of data for processing in real-time, therefore these are difficult to use as the source image of our system. Instead of this, we can use a camera with a wide angle lens. To obtain the same characteristics, in this paper, the road image acquired by a camera is transformed to Log Polar Mapping (LPM) image. The LPM image is similar to human vision system, high resolution in center of image and lower resolution as being far from center. It can gain a wide range information and reduce the volume of image data.

The LPM has two advantages for rushing out detection. The first one is polar coordinate transformation. While an observer moving forward, background flows turn to outside, and flows of a rushing object to camera turn to inside of this transformed image. We think

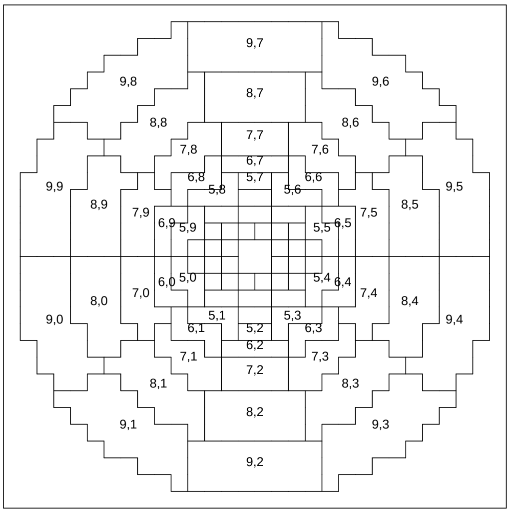


Figure 1: Lookup table representation of LPM ($30 \times 30 \rightarrow 10 \times 10$))

that this characteristic is suitable to detect. The second is logarithm coordinate transformation. It makes an image lower resolution as being far from viewpoint, so that it can reduce data for processing and it is easier to detect small flows in center of viewpoint than in far away area.

For fast coordinate transformation, we create lookup table that has u-v coordinate of every x-y pixels in advance. Transformation equations are

$$r_{\max} = \sqrt{(x_{\max} - x_c)^2 + (y_{\max} - y_c)^2} + r_{\min}, \quad (1)$$

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2} + r_{\min}, \quad (2)$$

$$\theta = \arctan(y/x) \quad (3)$$

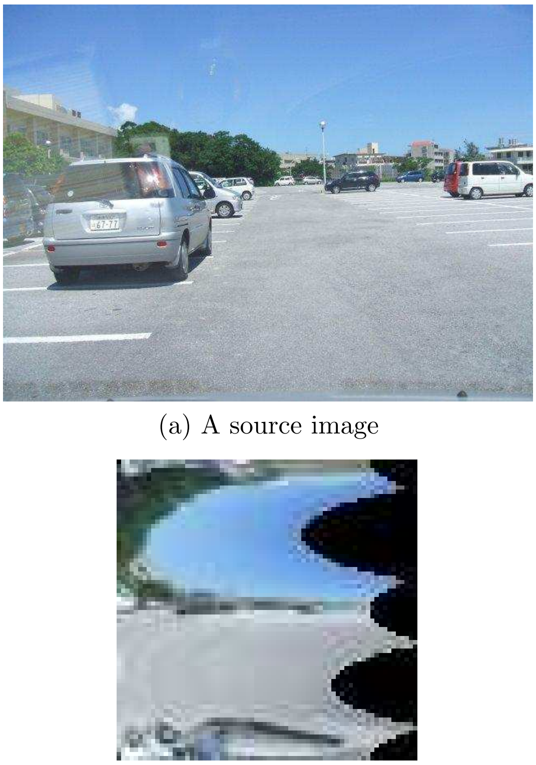
where (x_c, y_c) is view point in source image, $x_{\max}$ and $y_{\max}$ are the width and the height of source image, $r_{\min}$ is the value to control the logarithm slope, and

$$u = (u_{\max} + u_{\text{shift}}) \frac{\log r - \log r_{\min}}{\log r_{\max} - \log r_{\min}} - u_{\text{shift}}, \quad (4)$$

$$v = v_{\max} \cdot (\theta + \pi)/2\pi \quad (5)$$

where $u_{\max}$ and $v_{\max}$ are width and height of LPM image, u_{shift} is a parameter to shift coordinates to outer and this can use LPM image effectively with removing singularity of center. In this paper, we set $u_{\max} = v_{\max} = 70$, $r_{\min} = 300$, $u_{\text{shift}} = 4$. For fast coordinate transformation, we use lookup table (LUT) represented by transform equations of LPM to improve processing speed.

Using LUT, a source image is transformed to LPM image. When some pixels are transformed to the corresponding pixel in LUT, it takes pixels' average value. Inverse transform to x-y coordinate is not used for system but for visualization. Fig. 2 (a) illustrates a sample road image that is taken with camera mounted on a car, (b) is a LPM image.



(a) A source image

(b) LPM image

Figure 2: A road image (320×240) and LPM image (70×70)

2.2 Optical flow

We use optical flow method to extract velocity vectors of two time-scaled images. Optical flow gradient method is described as follows. When brightness $I(x, y, t)$ in every pixel (x, y) in time t does not change in $(t + \delta t)$,

$$I(x + \delta x, y + \delta y, t + \delta t) = I(x, y, t), \quad (6)$$

$$p\frac{\partial I}{\partial x} + q\frac{\partial I}{\partial y} + \frac{\partial I}{\partial t} = 0 \quad (7)$$

where $\delta x/\delta t = p$, $\delta y/\delta t = q$. To determine these values, it is needed to add other conditions. In this paper, we add a restrict condition that minimize all flows' changing values, and calculate flow vectors (p, q) iterately.

Table 1: GA parameters

Generation	100
Population	40
Offspring	20
Percentage of mutation	30 %

Table 2: NN desired output signals

Inputed flows	Desired output signal
Safe	0
Danger	1

2.3 Neural Network

The flow vectors acquired by optical flow are affected not only by objects we want to detect, but also by camera-self or other movements. LPM image has advantages to detect moving object from background flow as mentioned in Section 2.1. To ease these effects, we use NN to train flow vectors (p, q) of every pixels. NN outputs a judgment signal of road state $s = [0, 1]$.

The number of input neuron is 9,800($= 2 \times 70 \times 70$) that is the number of flow vectors p and q in input layer, 10 in hidden layer, and 1 that is a warning signal in output layer. We use sigmoid activation function in hidden and output layers. Fig. 3 shows three-layered NN structure.

NN is trained by genetic algorithm (GA). Table 1 shows GA parameters. The error function E for NN training is

$$E = \sum_{f=1}^{f^t} \mid s - s^d \mid \tag{8}$$

where f^t is the frames number, s is an sinal value, and s^d is a desired signal (0 for safe situation or 1 for dangerous situation) of trained data showed in Table 2. We prepare two values to judge ability of NN; a learning threshold value E^t_{lim} and a detection threshold value E^d_{lim}. If E is less than E^t_{lim}, NN training process is considered to be successful. After training of NN, the untrained data are inputted and tested whether NN is able to detect situation correctly. If the error between signal value obtained from untrained data and desired signal value is less than E^d_{lim}, the NN is considered to be able to detect the untrained situation.

3 Experiments and Results

To confirm the effectiveness of the proposed method, we experiment using actual movies. We make an actual road situation that a man rushing out from left forward side to the center of road, and being recorded as movie images. In this experiment, we use

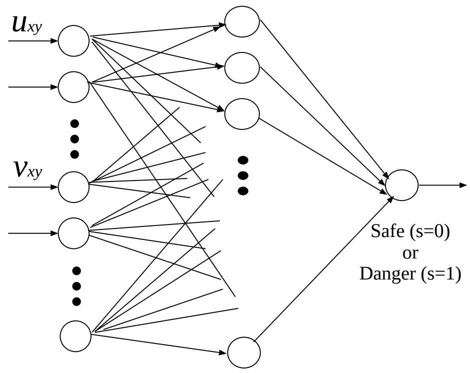


Figure 3: Neural Network: it receives flow vectors p and q as inputs, and outputs a judgment signal of road state ($s = [0, 1]$)

Table 3: Detection successful number

Image type	successful number
LPM	8 /10
shrinked	2 /10

the flow data of safe frames $f^t_s = 7$ and dangerous frames $f^t_d = 6$ for training, and safe frames $f^d_s = 3$ and a rushing-man frame $f^d_d = 1$ for detection. Here, $f^t = f^t_d + f^t_s$, $E^t_{lim} = 10^{-5}$ and $E^d_{lim} = 10^{-2}$. Fig. 4 and Fig. 5 show one of the trained frames as safe situation and one of the detected frames as dangerous situation. The arrows indicate the flow vectors in their point.

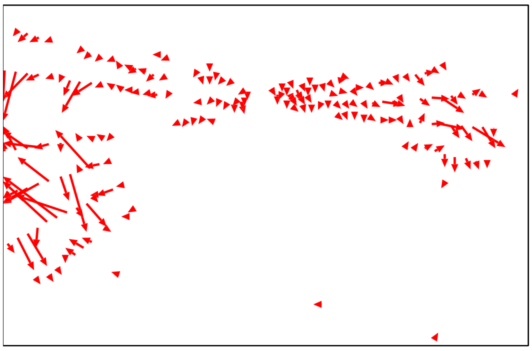
The experiment is tested 10 times with different random seeds. To confirm characteristics of detection with LPM images, we prepare shrinked images with the same size as LPM images. Fig. 6 shows the mean error of two tests with of LPM and shrinked image, and table 3 shows successful number of detections. From this, we can see that the proposed method with LPM image is easier to train and has higher ability of detection than the method using shrinked image.

The proposed method with LPM image has more successful number than the method with shrinked image.

4 Conclusions

In this paper, we proposed a man rushing out detection system for safe driving using LPM and NN. In the experiment with actual movie of the rushing man situation, both of training and detection, the proposed method with LPM images got better results than the method with shrinked images. As described above, there are high resolution in the center of LPM image

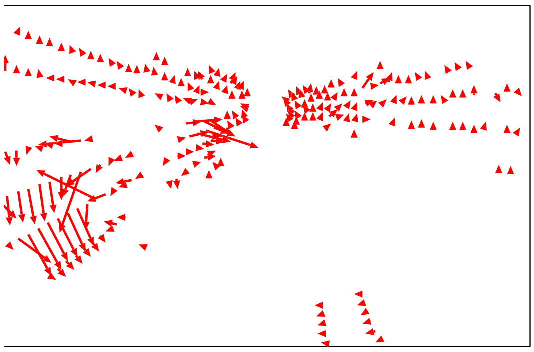
(a) Source image



(b) Flow vectors obtained from LPM images

Figure 4: A source image and flow vectors of a trained frame as safe

(a) Source image



(b) Flow vectors obtained from LPM images

Figure 5: A source image and flow vectors of a detected frame as safe

and it is easy to detect a flow of an object rushing to center. These results indicate the proposed method is suited to detect a rushing-out situation.

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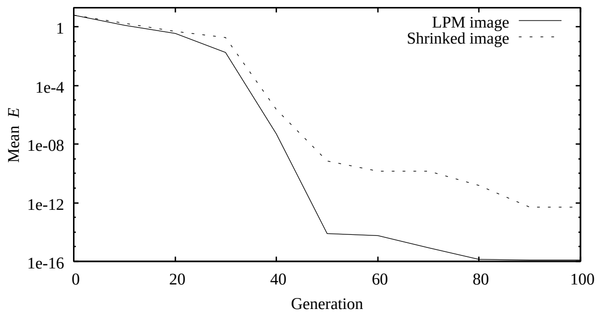

Figure 6: NN training curve