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A motion detection model inspired by hippocampal function and its applications to obstacle detection

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ABSTRACT

We have proposed a motion detection model, CA3–GU–CA1 (CGC) model, inspired by hippocampal function. The CGC model treats edges extracted from monocular image sequences, and detects motion of the edges on segmented 2D maps without image matching. In this paper, we propose an FPGA implementation of the CGC model, in order to achieve low power processing toward practical use. Then, we propose an obstacle detection algorithm using time-to-collision (TTC) based edge grouping. We have evaluated the performance of motion and obstacle detection by using artificial and real image sequences. The results show that the CGC model can achieve high detection rate in complicated situations, and can achieve accurate detection when using a high frame-rate. The proposed obstacle-detection algorithm can detect dangerous objects moving across based on a novel TTC estimation algorithm. Both motion detection and obstacle detection parts can operate at more than 1000 fps. The CGC model can also operate with a power dissipation of about 1.4 W based on the FPGA implementation.

1. Introduction

Motion detection is one of the key issues in collision warning systems for vehicles or mobile robots. There is much prior research that works by analyzing two-dimensional image motion, which is known as optical flow fields [1,2]. Among these, gradient models and block matching models have been popular and have been implemented in OpenCV [3]. However, these still have problems to improve the detection accuracy as well as to reduce the computational cost.

In our research, we aim to propose a collision warning system that can operate in high speed and with low computational cost. We have proposed such a system inspired by the neuronal propagation in the hippocampus in the brain [4]. The system treats edges extracted from monocular image sequences, and detects motion of the edges without image matching by using a so-called CA3–CA1 model [5,6]. Here, CA3 and CA1 are the names of hippocampal regions. We used this CA3–CA1 model to detect moving edges as spatiotemporal patterns, which are essential to the fuzzy-based danger evaluation in our system [4].

Because this CA3–CA1 model has a trouble with motion detection in complicated situations, we have proposed an improved model by introducing Gating Units (GUs) to solve the problem [7,8]. The proposed model is called CA3–GU–CA1 (CGC) model hereafter.

In this paper, we propose an FPGA implementation of the CGC model, in order to achieve low power processing toward practical use. Then, we propose an obstacle detection algorithm using time-to-collision (TTC) based edge grouping.

This paper is organized as follows. Section 2 introduce the concept of proposal. Section 3 describes the CGC model. Section 4 evaluates the performance of the CGC model by using artificial and real image sequences. Section 5 proposes an FPGA implementation of the CGC model for high-speed and low-power processing. Section 6 proposes an obstacle detection algorithm using time-to-collision (TTC) based edge grouping. Section 7 presents our conclusion.

2. Brief overview

If we denote the lens focal length, the pixel and world coordinates of objects by f, (i,j) and (X,Y,Z), respectively, we can find the following equations:

$$i = f\frac{X}{Z}, \quad j = f\frac{Y}{Z}, \tag{1}$$

here the origin is on the center of the image (Fig. 1). By differentiating these with respect to time, we obtain the following equations:

$$\frac{di}{dt} = \frac{f}{Z}\frac{dX}{dt} - \frac{fX}{Z^2}\frac{dZ}{dt}, \quad \frac{dj}{dt} = \frac{f}{Z}\frac{dY}{dt} - \frac{fY}{Z^2}\frac{dZ}{dt}. \tag{2}$$

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Note that $fX = iZ$ and $fY = jZ$, and these equations can be rewritten as follows:

$$v_i = \frac{f}{Z}v_X - \frac{i}{Z}v_Z, \quad v_j = \frac{f}{Z}v_Y - \frac{j}{Z}v_Z. \tag{3}$$

Therefore, we can detect image motion (v_i and v_j) and use Eq. (3) to estimate the velocities of objects in real world (v_X, v_Y, v_Z).

Time-to-collision (TTC), is defined as the time that is left until a collision occurs if an obstacle moves at a constant relative velocity [9,10]. TTC is an important indicator for danger evaluation, and can be calculated by $-Z/v_Z$. Here, the minus sign means that TTC has a valid value only when v_Z is negative; i.e., objects are approaching. It is possible to use Eq. (3) to estimate TTC if we can eliminate v_X and v_Y.

Because relatively stationary objects and those moving away are not dangerous, we use TTC to detect only approaching objects to reduce the computational complexity. Also, using TTC can make the best use of the CGC model. The CGC model detect some extra motion because it does not perform image matching. Using TTC can filter out these extra results of motion detection because the probability that these results have valid TTC value is very low.

3. CGC model for motion detection

The CA3–GU–CA1 (CGC) model proposed was inspired by the neuronal propagation in the hippocampus. The hippocampal formation consists of two principal regions: the dentate gyrus (DG) and the cornu ammonis (CA), where CA are usually divided into CA1, CA2 and CA3 by the anatomical difference. It has been clarified that the neuronal propagation in the pathway DG–CA3–CA1 contributes to the memory function [11]. This kind of propagation may preserve some information for a while as a spatiotemporal pattern, and may contribute to sequence coding [5,12].

According to physiological knowledge [13,14], CA2 neurons receive inputs in parallel with DG, and send inhibitory signals to CA1 neurons. Other research [15,16] indicated that the propagation between CA3 and CA1 is in two pathways: one is fast propagation in a CA3–CA1 pathway and the other is slow propagation in a CA3–CA2–CA1 pathway where CA2 neuron functions as a gate. We took some hints from these knowledge, and proposed the CGC model to treat monocular image sequences.

3.1. Model structure

The proposed model is shown in Fig. 2. In this model, four kinds of 2D maps are employed: actual image (AC), CA3, CA1 and GU maps, where AC map functions like DG in the hippocampus. These maps are divided into pieces based on a specified method and a piece of them is called a *unit* (of pixels). According to Eq. (3), if an object is approaching straight ($v_X = v_Y = 0$), the moving traces of its edges will radiate out from the center of the image because $v_i/v_j = i/j$. However, the radial center moves off the image center if objects have a non-zero v_X or v_Y. The shift Δd can be calculated by solving Eq. (3) for i when $v_i = 0$ (or for j when $v_j = 0$). We proposed a map-division method to detect objects with a non-zero v_X or v_Y. The details are described in a previous work [8].

The AC and CA3 maps are divided into two submaps with different map-divisions for motion detection in vertical and horizontal directions in the image plane, respectively. Each CA3 submap is related to two corresponding CA1 submaps that detect motion of edges in opposite directions, i.e. upward and downward or leftward and rightward.

Each AC unit has a *receptive field* (RF) as shown by the dotted line in the edge image in Fig. 2. If edges exist in a receptive field, the corresponding AC unit is activated, which is also referred to as "firing". This AC unit activity is propagated to the CA3–GU–CA1 network for motion detection. Each CA1 unit has a value that can decay linearly with time. We use the decay of CA1 value to measure the time that an edge takes to move from a unit to the neighboring one, which is called *travel time* in this paper. We calculate the velocity by using this travel time because the distance between two neighboring units is predefined.

GU is introduced into the model inspired by the function of CA2. The pathways of unit-activity propagation are shown by the arrows in Fig. 2, and the details of unit connection are shown in Fig. 3, where n indicates the spatial index of the units in one dimension. Each GU receives an excitatory input from the corresponding CA3 unit and an inhibitory input from the backward neighboring AC unit, which means that GU_n receives an inhibitory input from AC_{n-1}. Each GU sends an inhibitory input to the corresponding CA1 unit. The value of AC and GU is binary. CA3 has either a strong firing value (S) higher than the AC value or a weak firing value (W) lower than that.

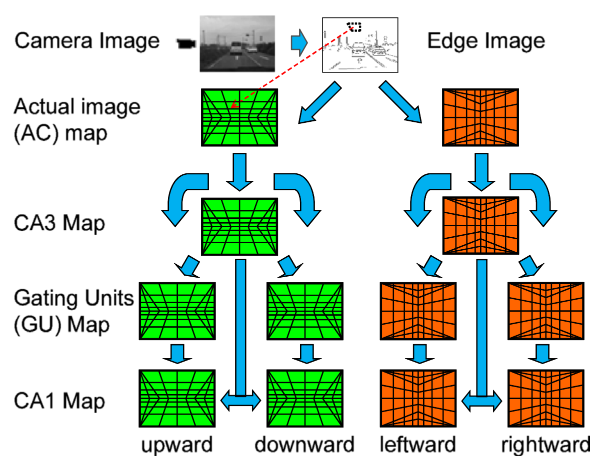

Fig. 2. Proposed motion detection model.

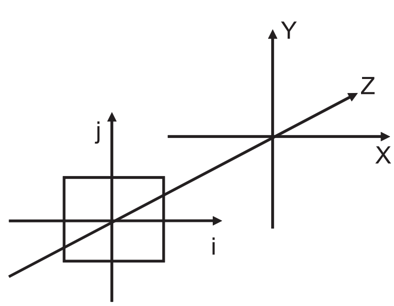

Fig. 1. Coordinate system.

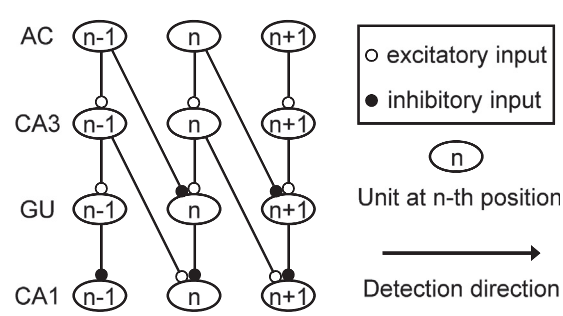

Fig. 3. Unit connection for rightward detection.