Neuromorphic Hardware Accelerated Lane Detection System

Shinwook KIM[†], *Member* and **Tae-Gyu CHANG**[†a)], *Nonmember*

SUMMARY   This letter describes the development and implementation of the lane detection system accelerated by the neuromorphic hardware. Because the neuromorphic hardware has inherently parallel nature and has constant output latency regardless the size of the knowledge, the proposed lane detection system can recognize various types of lanes quickly and efficiently. Experimental results using the road images obtained in the actual driving environments showed that white and yellow lanes could be detected with an accuracy of more than 94 percent.

key words: *lane detection, neuromorphic hardware, neural network, autonomous vehicle*

1. Introduction

Accurate lane detection is essential to realize an autonomous vehicle. The lanes marked on the road have various forms for each country and include their meanings according to colors and line notations. For example, yellow lanes separate vehicles moving in opposite directions as a center line, and white lanes separate vehicles moving in the same direction. Lane changing is allowed over dashed white lanes, and lanes cannot be changed in solid white lanes. Therefore, it is not desirable to recognize all the lanes as one kind, and it is necessary to be able to distinguish the recognition result according to the lane color and the lane shape, thereby providing meaningful information to the autonomous vehicle. However, until now, the existing lane detection system has focused on the recognition of the lanes itself rather than the recognition of the shapes and colors of the lanes.

The lane is mainly detected by the image sensors because it cannot be detected by using other automotive sensors such as radar or ultrasonic sensor. The quality of images acquired from image sensor depends on the quantity of light, the position of the light source, and the weather conditions [1]. In order to realize robust lane detection system in such a various environments, a large amount of computation is required. Moreover, since the image resolution and the Field-of-View (FOV) of a camera have become increasingly large in recent years, an explosion of computation has become inevitable. This trend makes real-time processing of lane detection more difficult. Conventional von Neumann architecture tried to overcome the limit of computation by

increasing the system clock frequency, optimizing the processing algorithm, and introducing the multi-core structure. At the same time, however, due to the rapidly increasing power consumption and heat generation, it was difficult to use in automotive industry.

Meanwhile, in recent years, neuromorphic technology, which imitates the information processing mechanism of the human's brain to learn and recognize the objects, has been studied steadily [2]. The neuromorphic system has the thousands of neurons implemented in hardware, and all of the neurons are connected in parallel so that they can accept the same inputs at the same time. Each neuron has a distributed local memory and performs the pattern matching continuously between the input vector and the pattern learned in the local memory. This structural advantage allows pattern recognition with lower system clock frequency and lower power consumption compared with conventional von Neumann architecture.

This letter proposes a lane detection system based on the neuromorphic system. The proposed lane detection system can learn various types and colors of lanes in the offline and detect the lanes marked in the road image using the learned lane patterns. In this process, since the image processing techniques used in the conventional lane detection system such as edge detection or Hough transform are not used, it is possible to detect the lanes with a small amount of calculation.

2. Background

A neuromorphic system is implemented with thousands of hardware neurons mimicking the recognition processes of information in the human's brain. The neuromorphic system has benefits from high parallelism, cognitive ability through the learning process, fault tolerant, constant latency, low clock frequency and low power consumption. Table 1 shows the comparison between conventional Von Neumann architecture using standard CPU and neuromorphic architecture.

All neurons in the neuromorphic system are connected in parallel to each other through a daisy-chain and are operated independently without a separate controller or supervisor [3]. Inside each neuron, there is a local memory, which stores a learned lane pattern in advance and calculates the distance at every each time a component of the input vector is received. By using this distance, the neuron outputs the result of classification based on k-nearest neighbor (KNN) [4] or radial basis function (RBF) [5], [6]. This series of pro-

Table 1 Comparison between Von Neumann architecture and neuromorphic architecture

|	Von Neumann Architecture using standard CPU	Neuromorphic Architecture
System Clock	High Frequency (≥GHz)	Low Frequency (≥MHz)
Power consumption	High (≥ 10W)	Low (≤ 0.5W)
Parallelization Mechanism	Multi-core structure	Identical neurons working in parallel
Software Complexity	High complexity programming to achieve the parallelism with multi-core structure	Learning by examples, Knowledge built in the neuron's local memory.
Cost	High	Low
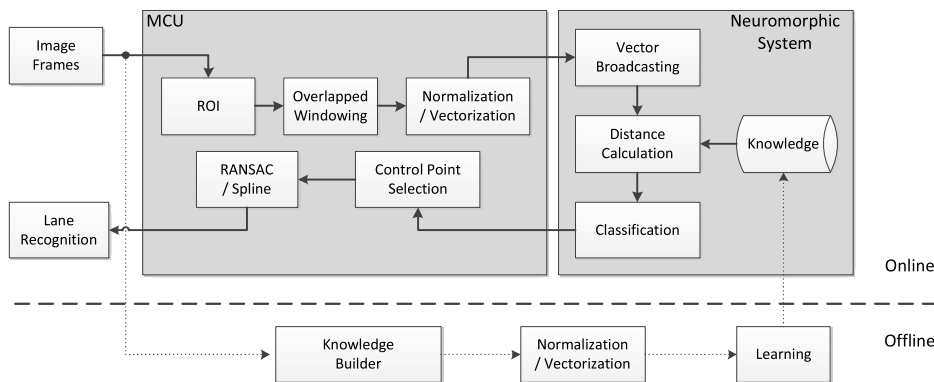
Fig. 1 Block diagram of the lane detection system based on the neuromorphic system

cesses makes the neuromorphic system look like a 3-layered neural network with a hidden layer.

3. Proposed Lane Detection System

The block diagram of the lane detection system based on the neuromorphic system is shown in Fig. 1. The proposed system is composed of microcontroller unit (MCU), neuromorphic system, and offline processes for knowledge generation.

Lane pattern acquisition and training process are performed offline in advance to generate the knowledge. The lane areas that are desired to be recognized by neuromorphic system are selected as a window size unit in the training images. The selected windows are made into a training vector set through min-max normalization and vectorization. By learning the training vector set into the RBF neural network, the reference lane patterns are stored in the neurons' memory and size of each neuron's receptive field is set to generate the decision space of the knowledge.

The MCU receives image frames from the image sensor to generate the input vector and deliver them to the neuromorphic system. The region-of-interest (ROI) is defined for each image frame for computational efficiency. Since the lanes in the image are placed at the lower portion of the vanishing point rather than being located at an arbitrary position, it is common to set the ROI to the lower portion of vanishing point. In this letter, in order to reduce the computational burden and increase the detection speed, the lane

search area is defined by specifying the lower part of vertical FOV as the ROI. Once the ROI is specified, a window for one vector size will slide with about 50% of the overlapping area and start generating vectors to be input into the neuron. First, the window is normalized to reduce the effect of light intensity and shadow. The normalized window is transformed into a vector form to facilitate calculating the distance between the input pattern and reference lane pattern learned in neuron's local memory. The generated vector is then delivered to the input of the neuromorphic system.

The neuromorphic system broadcasts the input vectors to all neurons and output the results of classification that are most similar to lane patterns learned advance in offline through the knowledge. The input vector is simultaneously transmitted to the whole neuron via the parallel bus. As the vector's components begin to be input, each neuron begins to calculate the distance from the lane pattern learned in the local memory and continuous to update the distance value until the input of the vector ends. When the calculation of the distance value is completed, the lane recognition result is outputted using that of distance value and the annotation information stored in the knowledge. In this process, because the input vector is transmitted to all the neurons simultaneously through the parallel bus, the number of neurons does not affect the response latency, and only the length of the input vector affects the latency. Therefore, when the number of neurons to be compared is large and the length of each vector is small, the total processing time of the neuromor-

phic system can be much faster than that of the conventional von Neumann based processing method.

The results recognized as white lanes or yellow lanes in the neurons are transmitted to the MCU, and the MCU selects the control points as reference for drawing the lane. For the control point selection, Random Sample Consensus (RANSAC) classification method is used in this letter [7], [8]. The RANSAC helps to accurately approximate lanes even in the presence of both correctly recognized and misrecognized patterns. On the other hand, Splines using the control points can also be used to generate the second-order or higher-order lane equations for curved roads [9], [10].

4. Experiments for Performance Evaluation

To verify the performance of the proposed lane detection system based on the neuromorphic system, the experiment with real daytime road images was conducted. The images used in this experiment were captured by RGB color image sensor with resolution of 1024×768. These images were taken in a city environment where various features ex-
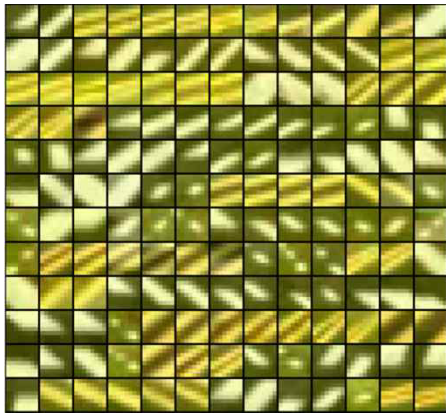

Fig. 2 Examples of white and yellow lane patterns learned in neurons

isted on the road, and were contained both white lane and yellow lane to distinguish between the different colors of lane. The neuromorphic system is implemented by CM1K chip developed by General-Vision Company [2], [3]. The CM1K is one of the most prominent neuromorphic system with 1,024 hardware neurons integrated inside and is commercially available on the market. For the MCU, NXP™ S32V234 SoC was used. The S32V234 SoC is one of the high-performance MCUs with Quad ARM Cortex-A53 processors and ARM Cortex-M4 processor. However, the proposed system minimized the use of MCU's computational resources to achieve low-cost computing. That is, the use of the MCU was limited to the interface with the camera sensor, the ROI setting, and the implementation of the RANSAC algorithm.

Figure 2 shows example of reference lane patterns learned offline in advance in order to recognize lanes of various shapes and colors in this experiment. To construct the reference lane patterns, 25 images including both white and yellow lanes were used as training data. In this training data, various types of lane patterns are extracted and learned in RBF neural network with annotations. As a result, a total of 165 reference lane patterns were generated and stored in 165 neurons to learn both white lane and yellow lane according to vehicle angle changes and various condition of brightness. Figure 3 shows some results of the lane detection in normal daytime condition. The original input images are shown in Fig. 3 (a). Figure 3 (b) shows the results categorized as the white and yellow lanes through the CM1K. The blue boxes and red boxes in Fig. 3 (b) represent the white lane and yellow lane categorization results, respectively. In this case, the sliding step size of 16×16 pixels window is 2 pixels on the X-axis and 32 pixels on the Y-axis, and from the 320th row, the ROI is defined for lane searching area. Since the output latency of the CM1K recognition for the one input vector is constant of $9.6 \, \mu s$, the total recognition latency used to classify the lane area in the ROI of one frame is $43.6 \, ms$. Figure 3 (c) shows the result of drawing
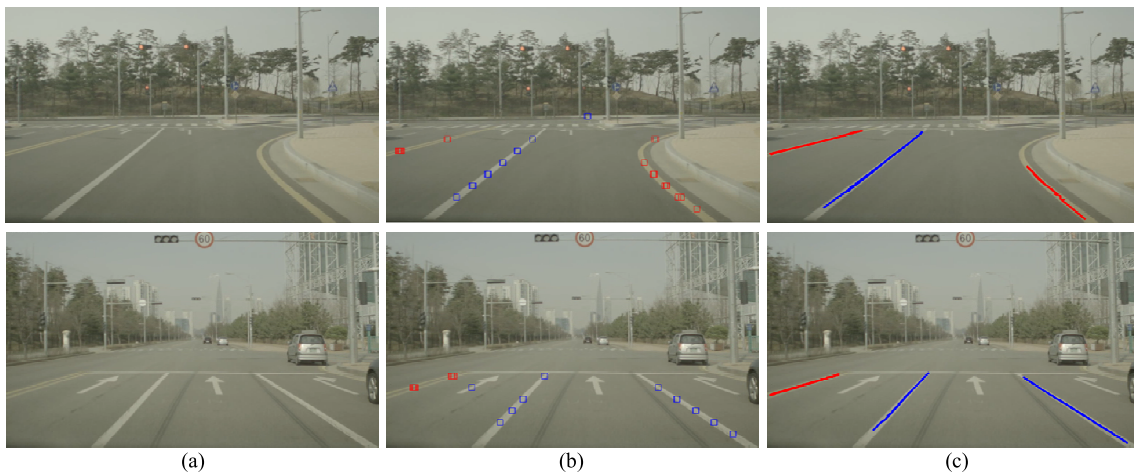

| (a) | (b) | (c) |

Fig. 3 Results of lane detection in normal daytime condition: (a) original input images, (b) results categorized as the white and yellow lane, (c) results of lane marking after the RANSAC
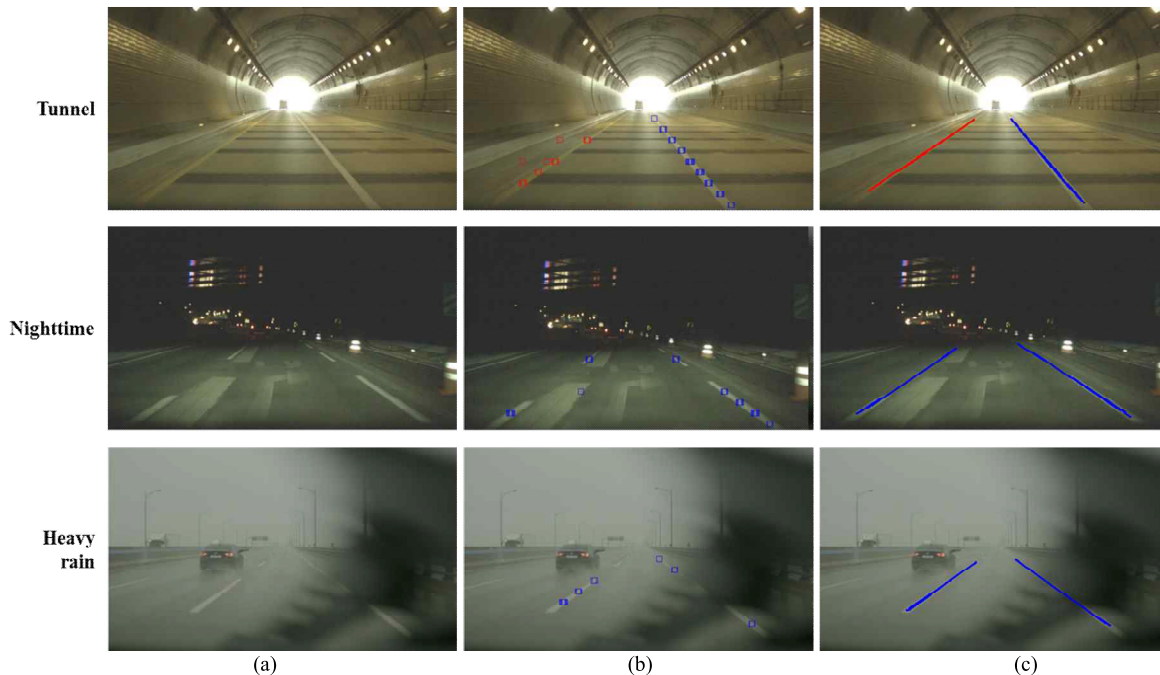
Fig. 4 Results of lane detection in harsh conditions: (a) original input images, (b) results categorized as the white and yellow lane, (c) results of lane marking after the RANSAC

Table 2 Lane detection performance in harsh conditions

Road Situations	Number of Lanes	Number of Misdetection	Detection Rate
Tunnel / City	3,840	100 frames	97.4%
Night / Expressway	3,982	20 frames	99.5%
Heavy Rain / Expressway	3,728	6 frames	99.8%

the lane after the RANSAC. The misrecognized patterns are excluded as outliers by RANSAC, and white lanes are drawn as blue lines and the yellow lanes are drawn as red lines in Fig. 3 (c). In the experiment, the line model RANSAC was used to remove the misrecognized cases and estimate the lane based on linear equations. To model the lane in RANSAC, two coordinates were randomly extracted and at least 10 iterations were performed under the assumption that the ratio of inlier was 80% or more. A total of 3,100 frames of road images were used to evaluate the detection performance in normal daytime condition, and 94 percent of lanes on road images were correctly identified as white and yellow lanes.

Additional experiments were conducted to verify how detecting performance can be changed according to the road conditions. The additional experiments include tunnel, nighttime, and heavy rain driving situations, which are considered harsh conditions in image sensor based lane detection systems. The experimental results under these harsh conditions are shown in Table 2 and Fig. 4. It is noticed that 97.4% of the lanes in the tunnel are recognized even though the contrast ratio of the yellow lane is lowered due
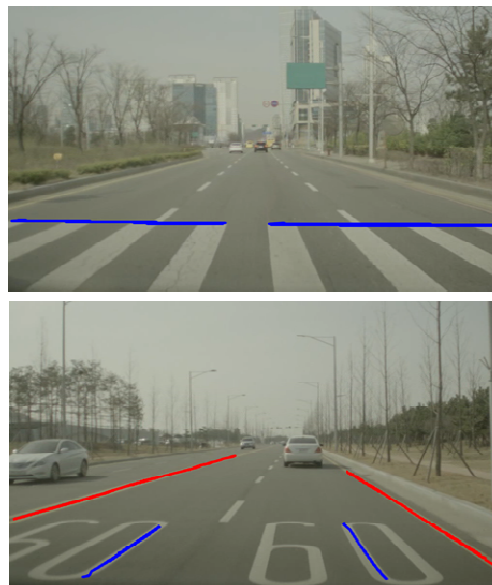

Fig. 5 Fail cases in lane detection due to crosswalk and characters drawn on the road surface

to the yellow colored sodium lighting. The result of the lane detection under nighttime driving condition shows that the proposed system can maintain the detection range even under the headlight condition. Furthermore, it can be seen that the background clutters are suppressed at nighttime, thereby increasing the detection rate for lanes. Even in the heavy rain condition, it is confirmed that the lane was detected as 99.8% accuracy despite the motion blur by raindrops and wipers.

Fail cases are shown in Fig. 5. Because the straight

line segment of the characters or crosswalk drawn on the road surface were recognized as lane pattern by the CM1K, the lanes were drawn at inappropriate locations in the image frame.

5. Conclusion and Discussion

We described the neuromorphic hardware accelerated lane detection system in this letter. Through the learning process, the neuromorphic hardware learned lanes of various shapes and colors and detected lanes in the input image through recognition process. In this process, the existing image processing algorithms were not used. Experimental results show that the proposed lane detection system can detect the lanes with accuracy of at least 94 percent in various environments including harsh conditions and 43.6 ms latency for recognition process in neuromorphic system.

However, some fail cases in lane detection can be observed in the images in which there are many straight line components similar to the lane, such as a crosswalk sign or characters drawn on the road surface. In order to overcome this phenomenon, it is necessary to study the lane patterns using the additional context or to improve the classification method such as the RANSAC.

Acknowledgments

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