

Bio-inspired visual information processing – the neuromorphic approach

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Abstract: - This paper describes the bio-inspired visual information processing by neuromorphic system, mimicking the primitive behaviour of visual cortex. The neuromorphic components are investigated for implementation of the visual signal selectivity of cortex, based on the CMOS conductance-based synaptic connections and neurons of Hodgkin-Huxley formalism. The proposed neuromorphic system exhibits the biologically plausible function mimicking the cat's visual cortex experimentation of Hubel and Wiesel. The detection of vehicle object or human head figure demonstrates the feasibility of vision applications.

Key-Words: - neural networks, CMOS, vision, neuromorphic, visual cortex, simple cell, Hodgkin-Huxley formalism

1 Introduction

There have been many works proposed recently for neuromorphic circuits and system, by mimicking both the functional and physiological characteristics of biological systems. We describe here the bio-inspired implementation of primary visual cortex, based on the neuron of Hodgkin-Huxley formalism and the visual cortex experimentation of Hubel and Wiesel. In this paper, the elements of neuromorphic implementation of visual cortex are presented with the orientation tuned map of synaptic weights and the spiking neuron, based on the electronically programmable MOSFET conductance.

The feasibility of neuromorphic VLSI visual cortex is investigated by simulated experimentation based on the CMOS 0.18 μ m technology, with demonstrated vision applications of detecting vehicle object or human head figure.

2 Primary visual cortex function and bio-inspired spiking neuron based on CMOS circuit

The physiological studies about visual cortex from the investigation of cat's striate cortex by Hubel and Wiesel have confirmed the consensus of knowledge [1], though there are many models about visual cortex. The idea on the primary visual cortex of simple cell motivated various theories of object recognition from characters to complex natural images [2]. For an idea of neural system implementation, the research about neurophysiology introduced the principles and demands of biologically

plausible electronic implementation. In this paper, we propose the new way of implementing the neuromorphic VLSI for the primary visual cortex, inspired by the ideas on the primary visual cortex by Hubel and Wiesel's experimentation and the neurophysiological model of neuron by Hodgkin and Huxley[3]. The design

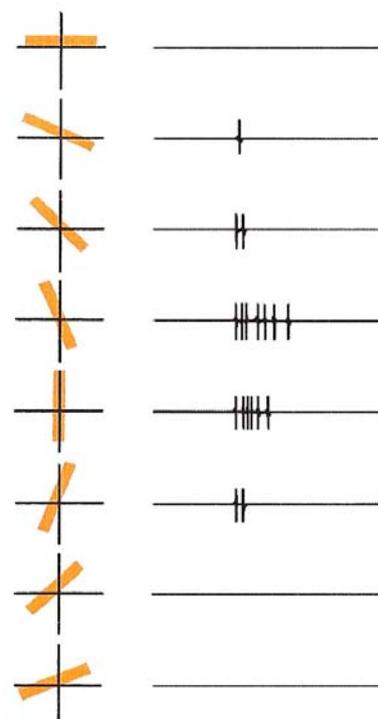


Fig. 1. Responses of the cat's cortex to shining a rectangular slit of light, in various orientations [1] motivation is from the well-known experimentation of simple cell in Fig. 1 by Hubel and Wiesel. The

experimentation of spike burst with static line is aimed to mimick, while there is another experimentation of complex cell based on moving stimulus by Hubel and Wiesel.

The controlled conductance by CMOS transistors is used as an element of our neuromorphic system, which have been studied for the biologically plausible analog-mixed neural networks VLSI [4, 5].

2.1 Neuromorphic neuron based on voltage-controlled CMOS conductance

The Hodgkin-Huxley (H-H) formalism is a widely adopted idea of neuron's biophysical characterization and dynamics. An electrical equivalent circuit model of Fig. 2 (a) is known as the empirical model of H-H formalism, which describes quantitatively the dynamics of the voltage-dependent conductance. Although most of

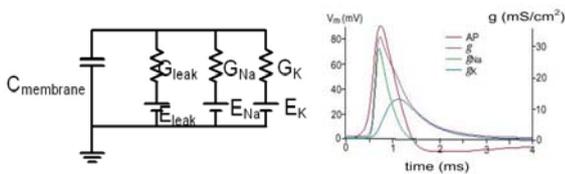


Fig. 2. (a) An electrical equivalent circuit of a neuron, Hodgkin-Huxley formalism (b) dynamics of asynchronous spike and refractory period vs. the membrane potential [3].

particular neural networks tasks do not exhibit any major advantages based on H-H formalism, asynchronous spikes are considered as a principle element of high level or large scale neural computing system [4, 8]. The H-H formalism is widely of interest for its biophysical dynamics, though its complexity in computation is prohibitively high. Hence, asynchronous dynamics of the H-H formalism is adopted as the idea of neuron model. An empirical mathematical formalism models dynamics of each conductance element as

$$\begin{aligned} G_{ion} &= G_{ionmax} \cdot x \\ dx/dt &= \alpha(b - x) \\ i_{ion} &= G_{ion}(V_m - E_{ion}) \end{aligned} \quad (1)$$

where b is the sigmoid function of membrane potential. V_m is a membrane potential and the overall dynamic modeled by an Action potential and related ionic conductance. Functional components of eq (1) are controlled conductance, multiplication, addition (or subtraction), and differential equation. The differential equation in eq (1) can be implemented by the low pass filter, which induces a delayed response.

The overall dynamic behavior of biological neuron is illustrated by the ion-based conductance controlled by

membrane potential (or Action Potential), with the illustrated dynamics of conductance in Fig. 2(b) [4].

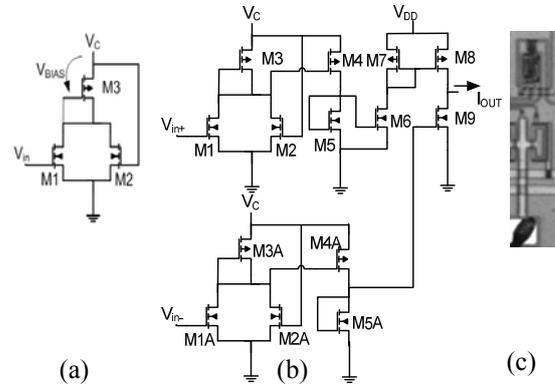


Fig. 3. (a) Voltage-controlled linear conductance by a pair of MOSFETs in the triode region, (b) the tunable linear transconductance circuit, (c) the chip photograph of CMOS transconductor.

A circuit of Fig. 3 (a) was proposed as a voltage-controlled linear conductance circuit by a PMOS transistor and a pair of identical NMOS transistors M1 and M2, while the conductance of MOS transistors is one of essential components in the analogue circuit design. The circuit of Fig. 3 has been investigated for various neural networks applications, from implementing synapses to neurons [4, 5].

The drain current I_D of M1 and M2 can be expressed as

$$I_{D1} = \alpha [(V_{GS} - V_{TH})V_{DS} - V_{DS}^2/2] \quad (2)$$

$$I_{D2} = \alpha [(V_C - V_{TH})V_{DS} - V_{DS}^2/2] \quad (3)$$

where $V_{GS} = V_{inDC} \pm \Delta V_{in}$ is the gate-source voltage of transistor M1, $V_{DS} = V_C - V_{BIAS}$ is the drain-source voltage of transistors M1 and M2, V_C is the tuning voltage of transconductance, and V_{inDC} is the DC offset of input voltage. Hence, V_{DS} is $(V_C - V_{BIAS})$ and the total current I_D is determined by

$$\begin{aligned} I_D &= I_{D1} + I_{D2} \\ &= \alpha(V_{GS} - V_{BIAS} - 2V_{TH})(V_C - V_{BIAS}) \end{aligned} \quad (4)$$

As the repeated two circuits in Fig. 3(b) operate in the same condition, the output current I_{OUT} is

$$I_{OUT} = Gm \Delta V_{in} \quad (5)$$

where $I_{OUT} = I_{D3} - I_{D3A}$. The transconductance circuit of Fig. 2 (b) can be used as a programmable conductance of

neuron's ion-channel or a synaptic connection with pulse/spike inputs.

2.2 Spiking neuromorphic circuit mimicking the primary function of visual cortex

The tuning properties of orientation selectivity have been believed to play the key role for perception in visual cortex. As shown in Fig. 1, the tuning of specific neurons to the orientation of visual stimulus probably depends on the tuning features after passive or active learning for the earlier processing of natural image. The rule we assume is very simple as illustrated in Fig. 4, though some modifications are likely necessary for being more plausible to the natural system. Here, the tuned feature map (or connection) of 5x5 synaptic weights is based on the reference stimulus to match, with the minor adjustment depending on the output. The tuned feature map of vertical orientation is illustrated in Fig. 4 (b), with the synaptic connections to 24 neurons (visual sensor, equivalent to a pixel) and itself. The synaptic weights of Fig. 4 (b) are in the ratio of (1 : -0.6 : 0.1 for black : grey : white) The six types of input stimulus (50x50 pixels) are experimented with the feature map (as synaptic connections) and spiking neurons (Fig. 5) based on H-H formalism.

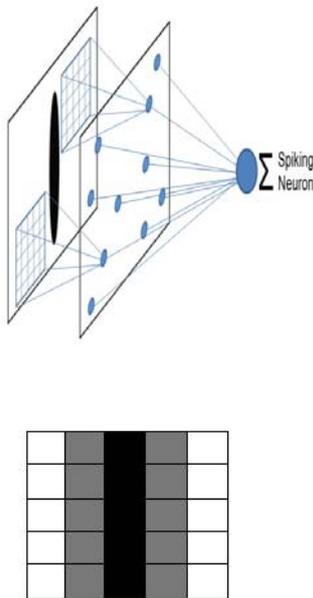


Fig. 4. The artificial primary visual cortex model with orientation selective synaptic weights to mimick the simple cell.

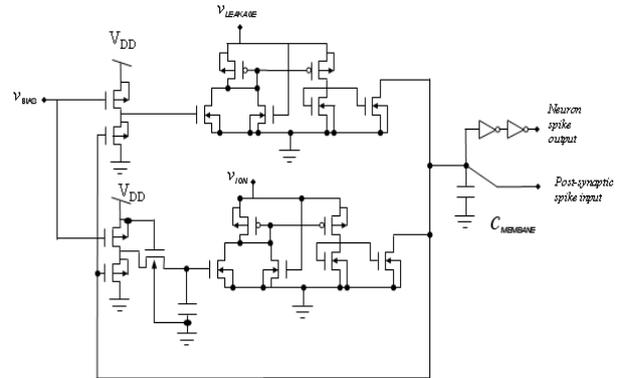


Fig. 5. VLSI neuron based on Hodgkin - Huxley formalism, using controlled CMOS conductance

The neuron model of Fig. 5 exhibits as the asynchronous spiking neuron with the refractory period, based on the dynamics in Fig. 2. The VLSI neuron of Fig. 5 is implemented by CMOS transconductance circuit of Fig. 3 in 0.18µm CMOS technology. The spike burst output of Fig. 6 is observed by SPICE simulation, where the neuromorphic visual cortex mimics the biological spike burst of Fig. 1 from the experimentation work of Hubel and Wiesel.

The feasibility of bio-inspired neuromorphic system is demonstrated with its plausibility to primary simple cell function of visual cortex as exhibited in Fig. 6. The tuned feature characteristics of other orientations (- 45°, 25°) are evaluated with the consistent outcomes as expected in the original experimentation of Fig. 1.

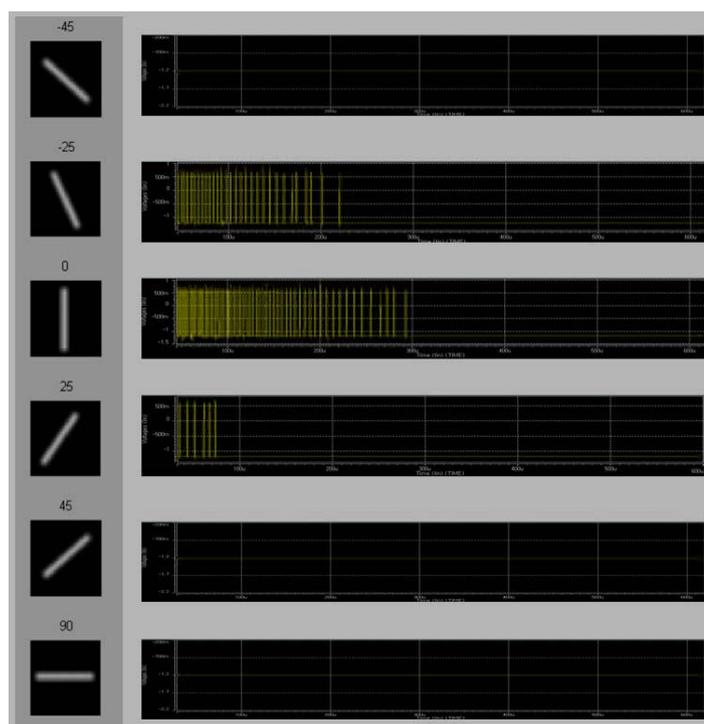


Fig. 6. The simulated spike burst of the VLSI visual cortex to stimulus in various orientations.

3 Bio-inspired visual information processing and application to object detection

The visual signal processing, particularly for vision application has been widely investigated, however, there is always a challenge such as the robustness to environmental change [7]. The proposed bio-inspired processing is applied to example cases for evaluating its feasibility, as animal or human usually has the reasonable robustness. The previous research demonstrated the robustness to a certain application of object detection, i.e. the vehicle license plate detection. The license plate detection was investigated for the flexible detection based on the rectangle with the right angle, regardless of the aspect ratio or the whole size. It is based on the particular selective response to orientation at the right angle, i.e. presenting both components of horizontal and vertical orientation. It demonstrated the robust detection under some environmental interferences such as the decorating shiny metal chain edge of license plate, in addition to detecting various sizes [6]. In this paper, the application of multi-directional selectivity is investigated

for the object detection on the road and human head detection.

3.1 Vehicle object detection

There has been growing research interests and demands on vehicle or pedestrian detection for intelligent transportation system or CCTV with the video analytic [9, 10]. In this paper, the bio-inspired signal processing is evaluated for detecting the vehicles from the visual data from the outdoor CCTV. The primary functional behavior is applied to locate the artificial object on the road, which is with the texture of particular directional angles. The operation principle is to extract the area of object, by removing unwanted information like illumination level, other shapes and etc. The outdoor CCTV image is subject to the environmental illumination changes from the cloud or the time of day. The difference of light condition is very different from the day and the night.

The basic system of Fig. 7 is evaluated for the feasibility of bio-inspired visual signal processing for various object types from passenger car to truck, and bikes.

The test images were taken from a CCTV with IP (internet protocol), which is located at the local road side. The basic system of Fig. 7 is based on the simple histogram calculation of bio-inspired direction processing of the image, where the processing of each direction is similar to the principle in Fig. 4. The size of array for each direction is 9x9, with elements mostly [2, -0.5, -1, -1.5]. An example of typical weights is

```

0.0 0.0 0.0 0.0 -1.0 -0.5 1.5 -0.5 -1.0
0.0 0.0 0.0 0.0 -1.0 -0.5 2.0 -0.5 -0.0
0.0 0.0 0.0 0.0 -1.0 2.0 -0.5 0.0 0.0
0.0 0.0 0.0 0.0 -1.0 2.0 -0.5 0.0 0.0
-1.0 -1.0 -1.0 -1.0 9.0 -1.0 -1.0 -1.0 -1.0
0.0 0.0 -0.5 2.0 -1.0 0.0 0.0 0.0 0.0
0.0 0.0 -0.5 2.0 -1.0 0.0 0.0 0.0 0.0
0.0 -0.5 2.0 -0.5 -1.0 0.0 0.0 0.0 0.0
-1.0 -0.5 1.5 -0.5 -1.0 0.0 0.0 0.0 0.0

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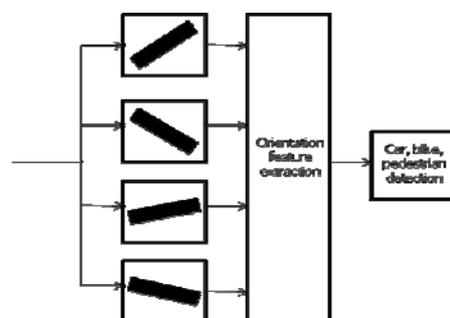


Fig. 7. Basic system configuration of bio-inspired visual information processing

Fig. 8 shows one of the CCTV image taken in the evening. The image is considerably blurred due to lack of illumination while artificial illumination such as headlight of vehicle acts as strong signal input. Background objects are also visible in the image. The corresponding histogram for the image is seen in Fig. 9, there isn't any distinctive feature from the histogram that may be used to detect the vehicle in the image. However, once this is processed in the proposed system using bio-inspired approach to detect the direction features, Fig. 10 is obtained. The sub-sampled image of 180X120 is used for detecting the directional feature of the captured image of 720x480. Even with inspection by eye, there is high density of directional feature where the vehicle is as there are lot of edges since it is a rigid object. And the histogram for the processed image, Fig. 11, shows that there are distinctive parts of the histogram which represents the vehicle. Appropriate threshold then gives successful detection of the target object as seen in Fig. 12. The proposed system performed successful detection of the object even though the overall illumination was low (since it was night) and other strong signals present such as background objects and lights from headlight.



Fig. 8. Input image (720X480) from CCTV (IPNC) at night time

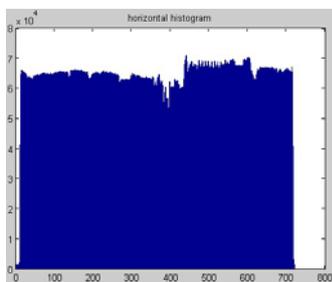
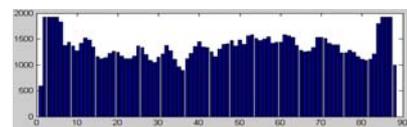


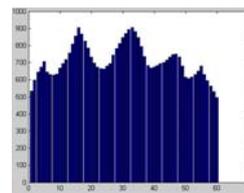
Fig. 9. Horizontal histogram of the image of Fig. 8



Fig. 10. Bio-inspired directional selective processed image of Fig. 8



a



b

Fig. 11. (a) Horizontal histogram of the processed image in Fig. 10, (b) vertical histogram of selected horizontal region from (a)



Fig. 12. Extracted region of detected vehicle based on the histogram analysis from Fig. 10 and Fig. 11

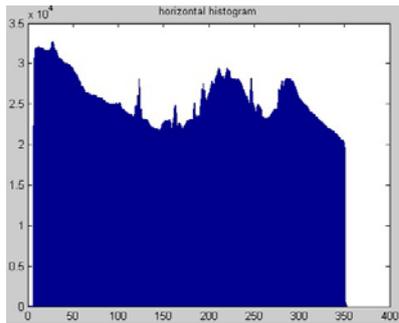
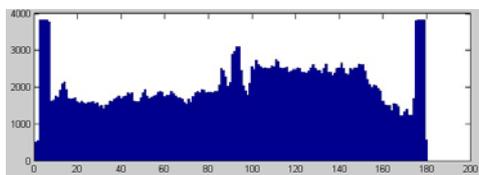


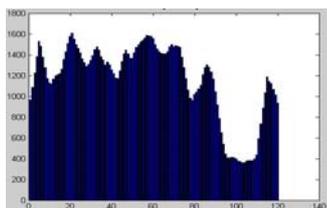
Fig. 13. Input image (720X480) from CCTV (IPNC) at day time and its horizontal histogram



Fig. 14. Bio-inspired directional selective processed image of Fig. 13



a



b

Fig. 15. (a) Horizontal histogram of the processed image in Fig. 14, (b) vertical histogram of selected horizontal region from (a)



Fig. 16. Extracted region of detected vehicle based on the histogram analysis from Fig. 14 and Fig. 15. The proposed system was tested for its robustness by using an image taken in daylight as seen in figure 13 with its corresponding histogram. The histogram of the input image has more notable features compared to the histogram of the image taken in the night. This may be due to overall illumination during daytime due to sunlight which causes different intensity on objects such as the target object and background objects. But this small variation is not enough to detect the target object so the proposed system was used to obtain figure 14, note the high density of directional features on the car compared to other parts of the picture. The histogram of the processed image, figure 15, shows much more distinctive features which were used to successfully detect the vehicle as shown in figure 16. The proposed system showed its robustness by not only successfully detecting the car in very different illumination condition than previously but also successfully detecting even though the vehicle is of different type.

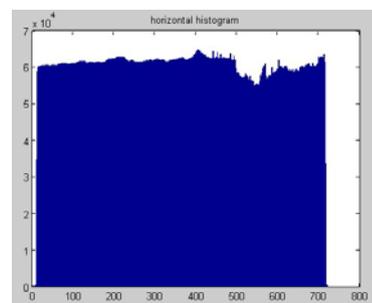


Fig. 17. Another input image (720X480) from CCTV (IPNC) at day time and its horizontal histogram



Fig. 18. Bio-inspired directional selective processed image of Fig. 17

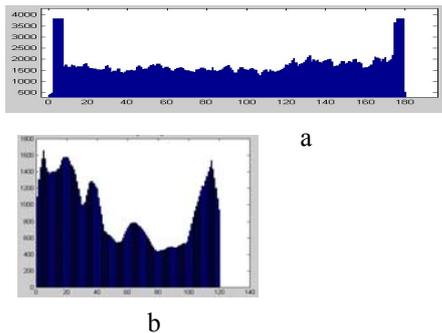


Fig. 19. (a) Horizontal histogram of the processed image in Fig. 18, (b) vertical histogram of selected horizontal region from (a)



Fig. 20. Extracted region of detected vehicle based on the histogram analysis from Fig. 18 and Fig. 19

Another image taken during the daylight was used to test the system as shown in figure 17 where corresponding histogram is also shown. The histogram is very similar to figure 9, as in this image, background objects are not seen. As background objects are not seen, the processed image, shown in figure 18, shows the outline of the car quite clearly even by inspection. And also the histogram of the processed image, figure 19, shows quite distinctive features where the target object is placed. The final detection of the object, as seen in figure 20, is somewhat clearer than previous images as the input image did not had any background objects or any variations in illumination in the image as experienced with the image taken in night time.

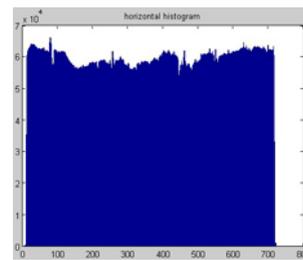


Fig. 21. Bike input image (720X480) from CCTV (IPNC) at day time and its horizontal histogram



Fig. 22. Bio-inspired directional selective processed image of Fig. 21

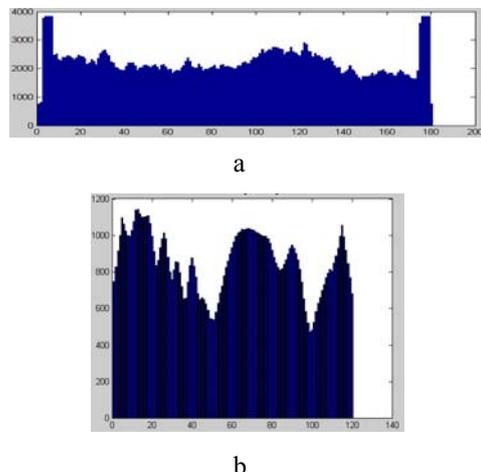


Fig. 23. (a) Horizontal histogram of the processed image in Fig. 21, (b) vertical histogram of selected horizontal region from (a)



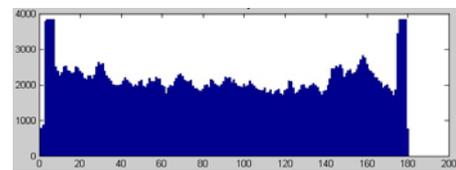
Fig. 24. Extracted region of detected bike based on the histogram analysis from Fig. 22 and Fig. 23



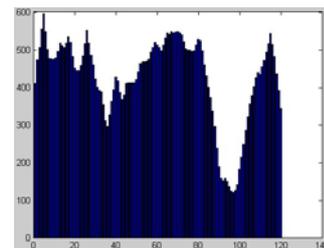
Fig. 26. Bio-inspired directional selective processed image of Fig. 25

As the system performed successfully in detecting cars, the system was tested at detecting motorbikes and a pedestrian.

The image of motorbike was taken using same CCTV during daylight, which is shown with its corresponding histogram in figure 21. The histogram, again, does not have any distinctive features as the size of the bike in the image is comparable to the background objects. The processed image, shown in figure 22, shows lot of directional features in the image and it is not quite clear to make out the shape of bike by inspection. However, there is high density of directional features as the shape of a bike is more complex than a car and, in addition; the biker also has complex shapes. So the histogram of this processed image, figure 23, shows distinctive areas where the bike is present, which is used to successfully detect the bike and the biker as shown in figure 24.



a



b

Fig. 27. (a) Horizontal histogram of the processed image in Fig. 25, (b) vertical histogram of selected horizontal region from (a)

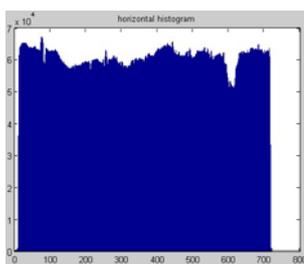


Fig. 25. Pedestrian input image (720X480) from CCTV (IPNC) at day time and its horizontal histogram



Fig. 28. Extracted region of detected pedestrian based on the histogram analysis from Fig. 26 and Fig. 27

Figure 25 showing the image of pedestrian taken during daylight and its corresponding histogram used to test the system. Again, there aren't much distinctive features that can represent where the pedestrian is. Although there is a part of the histogram where it's considerably lower, it is not enough to be used to detect the pedestrian. The processed image, figure 26, shows an outline of the pedestrian although it would be difficult to know that is pedestrian without seeing the original input picture. The density of directional feature on the pedestrian is comparable to the background object so the histogram of the processed image, figure 27, shows that it is a bit more difficult to see the distinctive feature at a glance as it was the case in previous images. However, the pedestrian is detected successfully as seen in figure 28.

The proposed system, using bio-inspired approach to detect directional features, to detect vehicles and pedestrian performed well in varying illuminations with other background objects even though the system is of a very simple kind.

3.2 Human head detection

There has been wide range of research in visual object detection and tracking for variety of applications [9]. The visual perception process is one area of growing interests, as we perceive objects with robust performance [10]. In this paper, the neuromorphic visual system is evaluated for detecting the human. There are two principles employed – first, the human object (particularly head) has high density of orientation components. The other principle is the head linked to torso. The summation of outputs from various orientations is utilized to implement the first principle, as illustrated in Fig. 29. The neural network detector of Fig. 30 is designed for second principle, where the weight values are only four levels. Considering the efficient CMOS neuromorphic VLSI implementation, all the weight values (or its dynamic range) are in the operating range of analog-mixed circuit based on voltage-controlled CMOS conductance.

The test images were taken by different cameras at the same time and place, with the same resolution (640X480). The image includes the upper part of a human on the glossy chair, with a Chinese landscape painting and toy dart board on the wall. The image of Fig. 31 was taken by a digital camera, while the image of Fig. 34 by a webcam. The horizontal histograms represent more complex situation considering the license plate detection [6], although it is clear for human vision to detect the head figure. The output of neural network detector of Fig. 30 represents the appropriate location, as in Fig. 33 and Fig. 36. The head figure is detected by the area selection

neurons (in this case, representing 10x13 reference points).

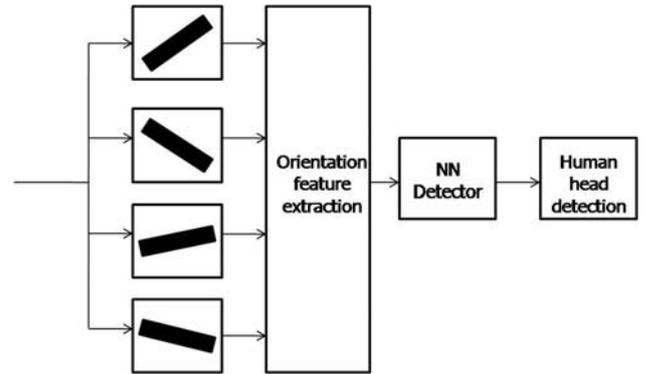


Fig. 29. Neuromorphic vision for human head figure detection, inspired by visual cortex

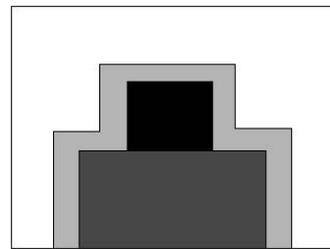


Fig. 30. Neural network detector of head-torso shape

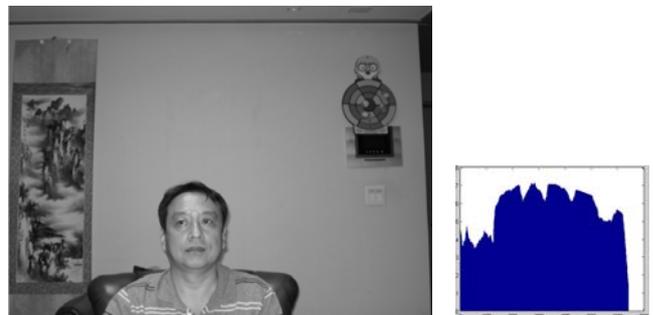


Fig. 31. Image from digital camera (640X480) and its horizontal histogram

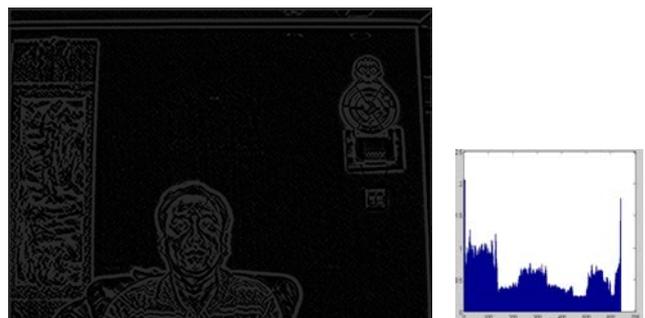


Fig. 32. Image of Fig. 31 with orientation selective processing and its horizontal histogram

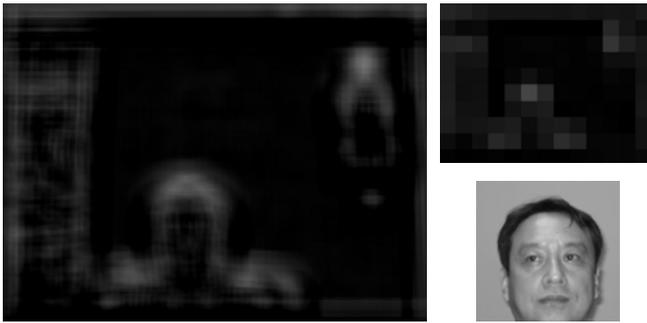


Fig. 33. Neural net detector output, Action level of detection neurons and detected human head object for the image of Fig. 31

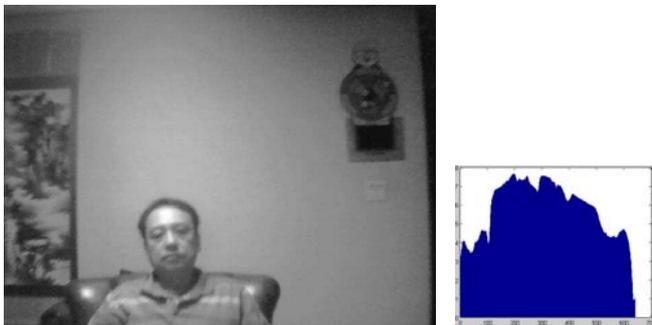


Fig. 34. Image from webcam (640X480) and its horizontal histogram

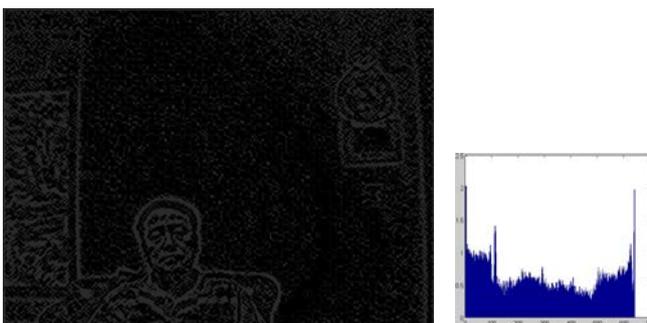


Fig. 35. Image of Fig. 34 with orientation selective processing and its horizontal histogram

The proposed system for human head detection is tested on more challenging environment of inside of a car. Fig. 37 and Fig. 41 shows the target in the car, where whole of the face is visible and only side view of the face is visible respectively. Side view of the face was taken to test the robustness of the system as some head detection algorithm fails when only side view of the face is seen since they rely on facial features for detection such as eyes and nose.

The orientation features extracted, Fig. 38 and Fig. 42, shows much more orientations detected compare to Fig. 32 and Fig. 35. Complex background and interior of the car with addition of the reflective clothing the target wore, there are many source for orientations. And as expected, the resulting image from the neural net detector does not show any distinctive shape of human as seen in previous input images, Fig. 33 and Fig. 36. However the system proves to be robust as it successfully detects the head for both the case; front of face and only side view face is visible and as seen in Fig. 40 and Fig. 44 respectively.

So the proposed system for head detection performed robustly and successfully in varying environment with complex background and foreground even if only side view of the face is seen. It is worthy to note that no training was required to detect the human head when most head detection requires training or certain conditions to be met for detection such as visible of facial features.

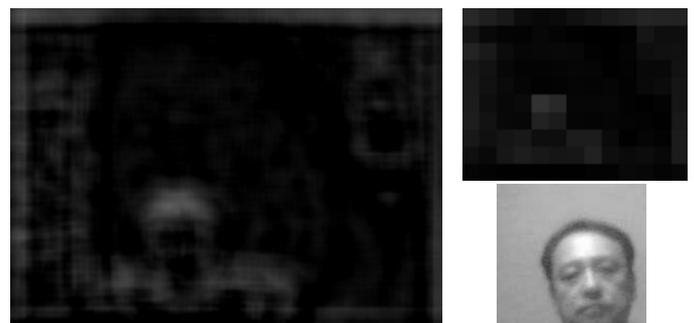


Fig. 36. Neural net detector, Action level of detection neurons and detected human head object for the image of Fig. 34



Fig. 37. Image (640X480) of a passenger in the back seat of passenger car



Fig. 38. Image of Fig. 37 with orientation selective processing and its horizontal histogram



Fig. 39. Neural net detector output for the image of Fig. 38



Fig. 40. Action level of detection neuron and the detected human head object for the image of Fig. 37



Fig. 41. Another image (640X480) of a passenger in the back seat of passenger car

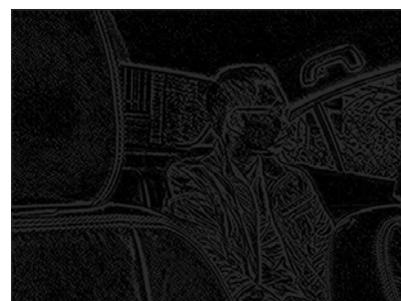


Fig. 42. Image of Fig. 41 with orientation selective processing and its horizontal histogram



Fig. 43. Neural net detector output for the image of Fig. 42



Fig. 44. Action level of detection neuron and the detected human head object for the image of Fig. 41

4 Conclusion

The bio-inspired neuromorphic vision is proposed as a feasible way of implementing the electronic hardware mimicking the primitive function of visual cortex, with application examples of object detection on the road and human head detection. The example cases are successfully demonstrated by neuromorphic processing of one-fourth scale of original image. The neuromorphic circuit design is based on the linear controlled conductance of CMOS transistors, and is feasible for intelligent image sensors with the primitive visual cortex function by bio-plausible neurons of 10 μ m x 10 μ m in 0.18 μ m CMOS technology.

The successful detection of vehicle or pedestrian and head figure is demonstrated with the simple bio-inspired principles, and the feasibility of neuromorphic vision is exhibited for various applications in limited environment, like embedded intelligent transport system.

Acknowledgement

This research was supported by the grant (09 Transport System-Future 02) from Transportation System Innovation Program funded by MLTM (Ministry of Land, Transport and Maritime Affairs) of Korean Government.

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