Smart Street Light towards Energy Saving and Neighborhood Security

Yuan XU[1], *Member, IEEE*, Tongsheng TANG[2], Yanghao ZHENG[2], Kezhong YANG[3], Zhiyong XIAO[1*], *Member, IEEE*

[1]College of Big Data and Internet, Shenzhen Technology University,
Shenzhen, 518118, P.R. China

[2]College of Information Engineering, Shenzhen University,
Shenzhen, 518000, P.R. China

[3]Shenzhen Nephotonics Technology Co. Ltd.,
Shenzhen, 518000, P.R. China

[*]Corresponding Author's email: xiaozhiyong@sztu.edu.cn

***Abstract*— Both street lights and surveillance cameras are very important to improve security at night in public places. These two types of facilities are often installed together but working independently with different purposes. With edge computing power, surveillance cameras can also be the eyes of street lights and work smartly to save electrical energy. This work presents a smart street light system that is able to detect pedestrians using surveillance cameras and adjust brightness intelligently. A new algorithm HDCV was developed in order to run human detection offline with limited edge computing resources. The HDCV algorithm employs histogram of oriented gradient (HOG) features to do fast detection and convolution network (CNN) based methods to do verification. The edge computing system was implemented with Raspberry Pi (RPi). The prototype demonstrated the capability to detect pedestrians accurately and resist interferences from animals. The system is estimated to save more than 30% electrical energy.**

***Index Terms*—Smart Lighting, Human Detection, CNN, HOG**

I. Introduction

Lighting is so important in human society that it consumes about 20% electrical power in the world, of which 5% is for public lighting [1]. As the internet of things (IoT) technologies are advancing rapidly, people set high expectations on smart lighting, which is a very important part of smart city [1-4]. The long term expectation on smart lighting is promising and exciting. Yet many proposed solutions are infrastructure scale and usually require sensors and central servers, which makes it less realistic in the near term. Some simple technologies, e.g. sound control, light dependent resistor (LDR) control, were already implemented into our daily life to save energy for lighting even before smart lighting concept was popular. However, these simple approaches are not very efficient since street lights in public places are idling for a large proportion of night time, e.g. there are no pedestrians on the road.

Many efforts were taken to improve the energy efficiency of street lights. Pyroelectric infrared (PIR) sensors were reported to detect people with very low standby power consumption [5]. But its detecting range is limited and easily interfered by animals. Microwave sensors or RADAR were also reported to detect pedestrians [6]. It is effective in detecting moving vehicles and walking people, but the sensors can only detect objects in motion, and cannot identify animals either. As computer vision technologies are developing rapidly, they draw a lot of attention in security surveillance. Surveillance cameras and street lights are two important elements in public places, and they are usually installed together, however, working independently. There will be opportunities if we can bridge the gaps between security surveillance and lighting. Effort to use image processing to detect pedestrians and vehicles was reported in [7]. However, the reported work was using Object-Level Frame Comparison (OLFC) method which applies K-means clustering algorithm to segregate images. This approach is basically to detect changes to reference images instead of doing object recognition, which is error prone because public places are subject to constant changes. Algorithms of histogram of oriented gradient (HOG) descriptors with linear support vector machine (SVM) classifiers were well established in human detection more than 10 years ago [8], but recently convolution network (CNN) based deep learning methods have been taking the lead in image recognition [9-10]. While CNN based approaches provide much better recognition accuracy, HOG based approaches run much faster in detection on the other hand.

In this work, we developed a smart street light prototype using Raspberry Pi 3 Model B (RPi 3B) as the edge computing unit. This prototype intended to maximize energy saving with surveillance cameras in public places dominated by pedestrians, such as neighborhood trails, parks and plazas. CNN based approaches are demanding heavy computing resources to do multiple layers of convolution, which makes it inappropriate under current edge computing capacity. A new algorithm was implemented in RPi 3B so that it can

978-1-7281-5650-7/19/$31.00 ©2019 IEEE

process 720P images at 30 fps, which is nearly minimum requirement for video surveillance. This algorithm is called HDCV since it does HOG-based detection and CNN-based verification to balance speed and accuracy. HDCV was designed to detect human beings only. Animals like dogs and cats will not interfere with the detection.

II. System Description

The whole smart lighting system is illustrated in Fig. 1. With edge computing system, surveillance cameras and lamps are no longer working independently. After collecting video images from surveillance camera, the edge computing system will process video stream to detect pedestrians, and sends control signals to lamp unit. It can also code and transmit data to internet so that authorized users can access the surveillance data, or to receive and execute instructions when necessary. Since human detection consumes most computing power of the edge, it is important to select an appropriate algorithm.

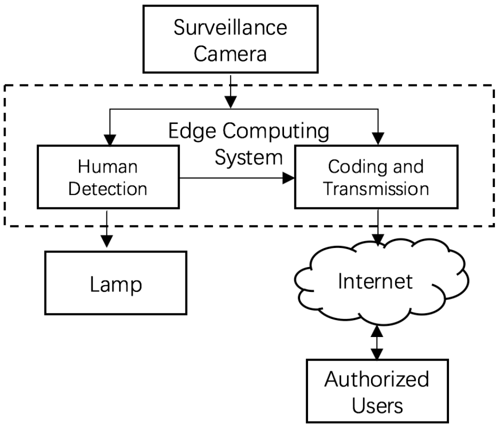

Fig. 1. Schematic of Smart Street Light System

III. Human Detection

Human detection for lighting is a very special case image recognition since the major challenges such as occlusions and background clutter are not likely to happen. The fact that the lighting control unit only cares about whether there are pedestrians but not the exact number of pedestrians further simplifies the problem. Although the tested VOC 2012 average precision (AP) for CNN based approaches were reported to be about 60-80% [10, 12] which is still far away from perfect, they are more than sufficient in lighting application. However, it is computationally expensive for all CNN based approaches since many convolution layers need to be computed. It poses a real challenge for edge computing. HOG based approaches have become popular since 2005 when Navneet Dalal and Bill Triggs first published their study on human detection using HOG descriptors and linear SVM based classifiers [8, 11]. This approach gave near-perfect separation on the original MIT pedestrian database and well balanced with accuracy and hardware resources, considering that this method was widespread more than 10 years ago and hardware performance has been improved greatly over the last decade. But unfortunately HOG based approaches easily confuse animals with people, which makes it less efficient to save electrical energy of lighting.

We developed a new algorithm HDCV in order to run detection with real time performance without sacrificing accuracy. The first step is to use HOG features to do fast detection. The flow chart of HOG feature extraction and detection is illustrated in Fig. 2. The HOG feature extraction can reach 30 fps for 720P images in RPi 3B, which uses Quad Core 1.2GHz Broadcom BCM2837 64bit CPU. There is false positive detection due to interference from animals at this step.

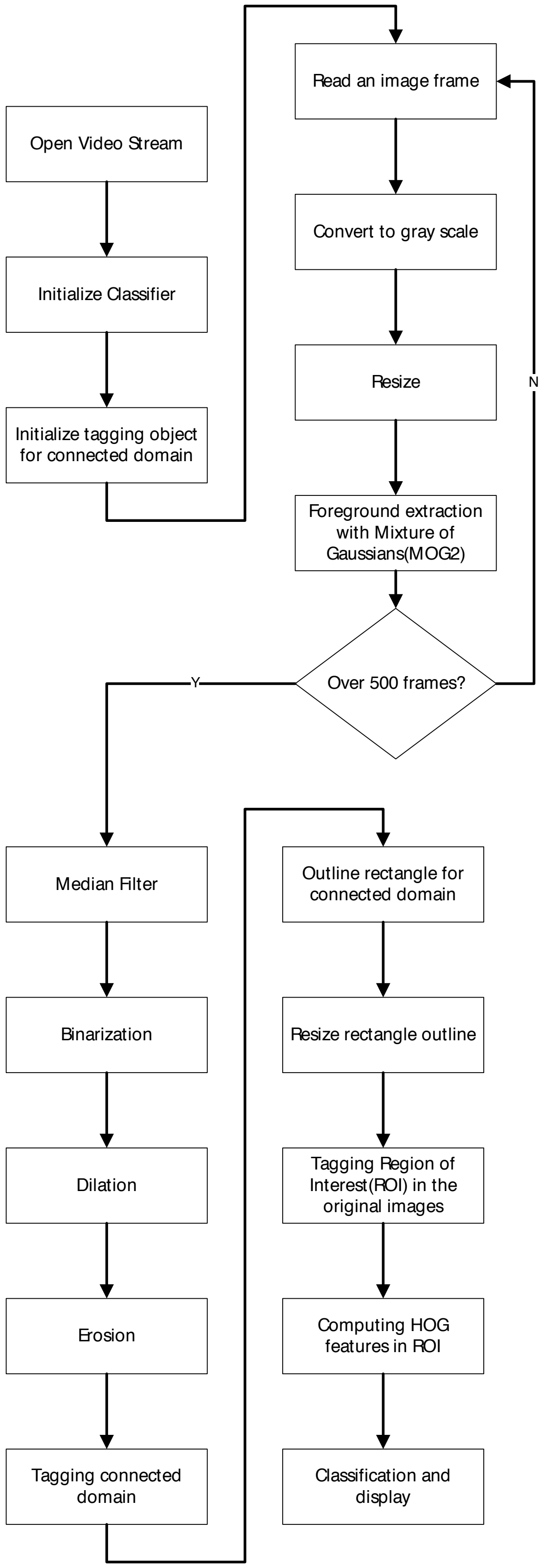

Fig. 2. HOG Feature Extraction of HDCV

In order to remove the false positive detection in the 1st step, we employ CNN to verify the results. We developed a holistic CNN similar to You Look Only Once (YOLO), which frames object detection as a regression problem to spatially separated bounding boxes and associated class probabilities [12]. Since we focus on human detection only, we've got only 1 bounding box and 1 associated class probabilities. In order to further improve the speed, images are resized to 224x224 as the initial input to the convolutional layers. There are in total 14 convolutional layers and 2 fully connected layers, as shown in Fig 3. Images will be devided to 14x14 grid cells. The grid cell size is 16x16 and the final output is a 14 × 14 × 6 tensor of predictions.

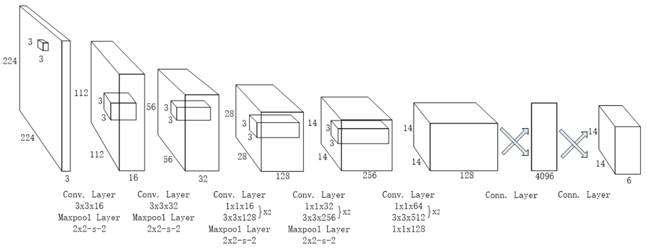

Fig. 3. Convolution Network of HDCV

IV. Implementation

RPi 3B is a single board computer with LAN and wireless connection in pocket size with well balanced cost and performance, which makes it ideal for edge computing in this work. Raspberry Pi camera module was selected for the surveillance system, which supports 1080 30fps, 720 60fps video modes. The camera module connects to RPi 3B with 15cm ribbon cable via CSI port. LDR module was also selected to sense the day light so that human detection will only be off in the day time. IR auxiliary light sources were installed to the surveillance system so that it can provide auxiliary lighting to improve image quality under low illumination. Light control signals and LDR signals are communicated through GPIO pins. There are 40 GPIO pins in RPi 3B, which offers huge flexibility in communicating with peripheral equipment.

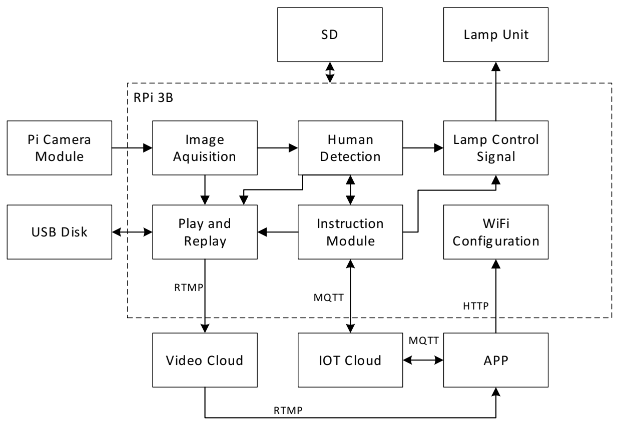

Fig. 4. Implementation

The whole system is illustrated in Fig. 5. Modules inside RPi 3B box are software modules, of which each runs on its own thread. Video stream is coded in H.264 format. APP will provide access and control to the smart light system for authorized users.

The photo of the physical part of RPi 3B is shown in Fig. 5. A signal line to the infrared auxiliary light source is also connected to a GPIO pin so that RPi 3B can control it. The assembly of the whole smart light system is shown in Fig. 6 and the photo of prototype is shown in Fig. 7.

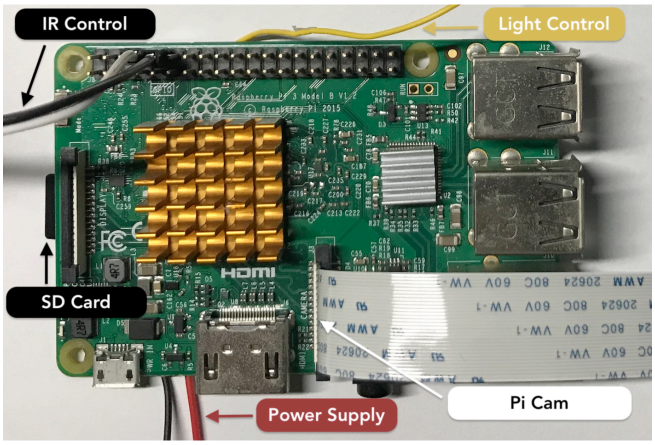

Fig. 5. Photo of RPi 3B

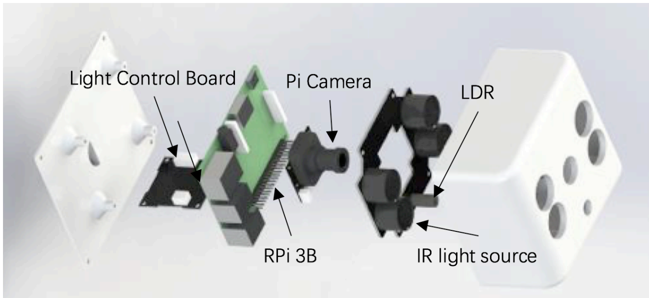

Fig. 6. Assembly of Smart Light System

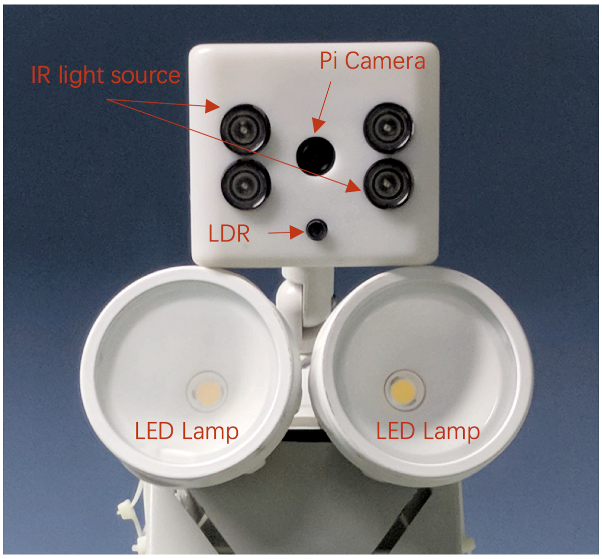

Fig. 7. Prototype of This Work

V. Experimental Results

A. Energy Saving

The average power consumption of the detection unit was tested to be about 5W, and the power of IR auxiliary sources is 8W. If we use 258W reported in [13] as the street light power consumption, and assume the street light will be on for 10 hrs at night and the idling time is more than 5 hrs. We further assume that the street light consumes only a third of its maximum power, it is estimated to save more than 30% electrical power with the smart street light, and it saves more energy as detected idling time increases, as shown in Fig. 8.

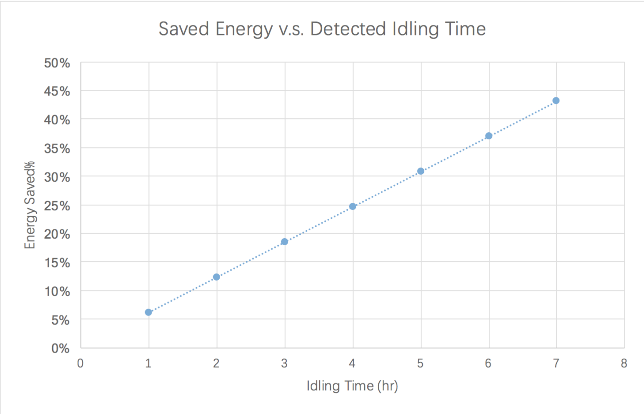

Fig. 8. Saved Energy v.s. Detected Idling Time

B. Human Detection

We also tested the human detection performance of the system. We also tested the lighting systems with different detecting techniques for reference. We collected 100 data points when people was passing through the system, and 100 data points when we had animals to pass through the system. The results were shown in Table I. The results showed that the system in this work can detect human accurately and will not be interfered by animals.

TABLE I. Human Detection Results

Lighting System	***Turn on by Person***	***Turn on Rate***	***Turn on by animals***	***False Rate***
Sound Control	78	78%	52	52%
PIR	86	86%	46	46%
RADAR	90	90%	84	84%
This Work	100	100%	0	0%

VI. Conclusion

This work combined surveillance camera and street light successfully to be a smart system, serving the needs of both security and lighting in the neighborhood. The HDCV algorithm was developed and implemented into the RPi 3B. The prototype demonstrated the capability to detect human accurately and resist interferences from animals. The system is estimated to save more than 30% electrical energy.

References

[1] M. Kuusik, T. Varjas, and A. Rosin, "Case study of smart city lighting system with motion detector and remote control," *2016 IEEE Int. Energy Conf.*, 2016.

[2] Zanella A, Bui N, Castellani A, et al. "Internet of Things for Smart Cities," *IEEE Internet of Things Journal*, 2014, 1(1):22-32.

[3] Müllner R, Riener A. "An energy efficient pedestrian aware Smart Street Lighting system," *International Journal of Pervasive Computing & Communications*, 2011, 7(2):147-161.

[4] A. Barghi, A. R. Kosari, M. Shokri, and S. Sheikhaei, "Intelligent lighting control with LEDS for smart home," *Smart Grid Conf.* 2014, SGC 2014, pp. 1–5, 2014.

[5] C. H. Tsai, Y. W. Bai, C. A. Chu, C. Y. Chung and M. B. Lin, "PIR-sensor-based lighting device with ultra-low standby power consumption," *2011 IEEE International Instrumentation and Measurement Technology Conference*, Binjiang, 2011, pp. 1-6..

[6] O. Tetervenoks, P. Suskis and J. Stegura, "Integration of microwave sensor into low cost indoor LED lamp — Element of smart lighting system," *2017 5th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE)*, Riga, 2017, pp. 1-4.

[7] Veena P C, Paulsy Tharakan, Hima Hridas, Ramya K, Riya Joju, and Ms. Jyothis T S. "Smart Street Light System based on Image Processing," *International Conference on Circuit, Power and Computing Technologies (ICCPCT)*, pp.1 – 5, March, 2016.

[8] Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*. Vol. 1. IEEE, 2005.

[9] Lecun Y, Bengio Y, Hinton G. "Deep learning," Nature, 2015, 521(7553):436.

[10] Ren, Shaoqing, He K, Girshick R, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." *Advances in neural information processing systems*. 2015.

[11] X. Yuan, L. Cainian, X. Xiaoliang, J. Mei, Z. Jianguo, "A two-stage hog feature extraction processor embedded with SVM for pedestrian detection", 2015 IEEE International Conference on Image Processing (ICIP), pp. 3452-3455, 2015.

[12] J. Redmon, S. Divvala, R. Girshick, A. Farhadi, "You Only Look Once: Unified real-time object detection," IEEE Conference ComputerVision and Pattern Recognition (CVPR), 2016.

[13] Yang C W, Nefedov E, Sierla S, et al. "Vehicle and pedestrian aware street lighting automation," IEEE, International Conference on Industrial Informatics. IEEE, 2015:1269-1274.