PORTOFOLIO

JANUAR KAILANI SUAEB

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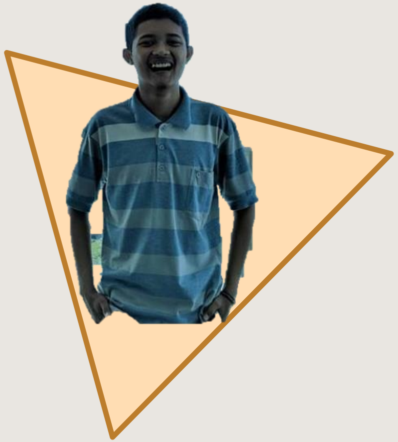
ABOUT ME



- Januar kailani Suaeb (Suaeb)
- Pamekasan, January 24th 1998
- Dusun Barat, Desa Gro'om Kecamatan Proppo, Kabupaten Pameksan
- Graduates from Mechatronics Engineering, Electronics Engineering Polytechnic Institute of Surabaya
- GPA 3.43 of 4

Have Excellent Programming, Mechanical Design, electronics and Winning Spirit. Therefore I want to develop my Engineering skills at Computer Vision, 3D mechanical Design, Control System and Data Analytic. And hopefully to put my competencies to the best use to contribute to organizational and individual developments.

083852011059

januarks14@gmail.com

januarks14

EXPERIENCE

Work Experience:

Wiring and Control at PT. PINDAD (Persero) (2018) / Internship

- Make an electrical assembly design for military vehicle Panser Komodo
- Make a design of control for automatic open/close ramp and roof door for military vehicle Panser Anoa
- Develop a security system for panser Anoa : Acoustic Warning System

Project Experience:

Develop Automatic Turret Gun With Deep Learning Technology (2018 – 2019)/ Final Projects

- Make a structure of Deep Learning with Convolutional Neural Networks
- Built Human Detection from Deep Learning model that have made
- Embedded all program to Prototype of Automatic Turret Gun

TECHNICAL SKILLS

Programming Microcontroller
Have experiences with AVR, ARDUINO and NI myRio

Computer Vision
Have experiences with OpenCV and MATLAB for Computer Vision

3D Mechanical Design
Have Experiences with INVENTOR and Solidworks for 3D Mechanical Design

Machine Learning
Develop ML for Computer Vision using casacde, SVM and CNN

COMMUNICATION SKILLS

COMMUNICATION SKILLS

Mother tongue(s)

- Maduranese
- Bahasa Indonesia

Other language(s)

English

An Implementation on Automatic Targeting System of 2-DOF Gun Turret

INTRODUCTION

Automatic turret gun is a military weapons system that can be used as a defense or attack device that runs automatically without being controlled by the operator (autonomus). In this project, Automatic turret gun can detect targets automatically with the help of computer vision technology. There are 3 types of computer vision methods implemented in this project, namely Haar with Cascade Classifer, HOG with SVM classifier and Convolutional Neural Networks.

Image of Automatic Turret Gun System prototype

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Design of Overall System

We build the gun turret prototype using a metal case with an airsoft gun mounted on top of the platform’s base. For high-level processing, we are using a highperformance personal computer with the specification of Intel Core i7 processor with 16GB RAM and GTX 1080 ti GPU based on Ubuntu 16.04 LTS operating system. For low-level, we use NI myRio as sub-controller connecting the motors, solenoid for triggering the gun, and sensors. The sensors contain two encoders of the dc-motor and proximity sensor for minimum and maximum each joint position.

The sub-controller is equipped with FPGA for real-time processing. The real-time is highly necessary for the control turret movement and sending feedback of position. A widely used PID control is used to control the motors. After highlevel processing such as tracking the desired object, the relative object position is sent from the PC to the subcontroller.

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Robot Operating System

ROS

In order to achieve the real-time interoperability between the Ubuntu machine to the LabView-based of the subcontroller, Robot Operating System (ROS) is used in this system. ROS needs to start a master node, which is the PC as a ROS server. Then the data can be sent in both directions as both systems support ROS. With this, using ROS in PC and LabView is expected to speed up the computational process in processing data without worrying much on the communication protocol.

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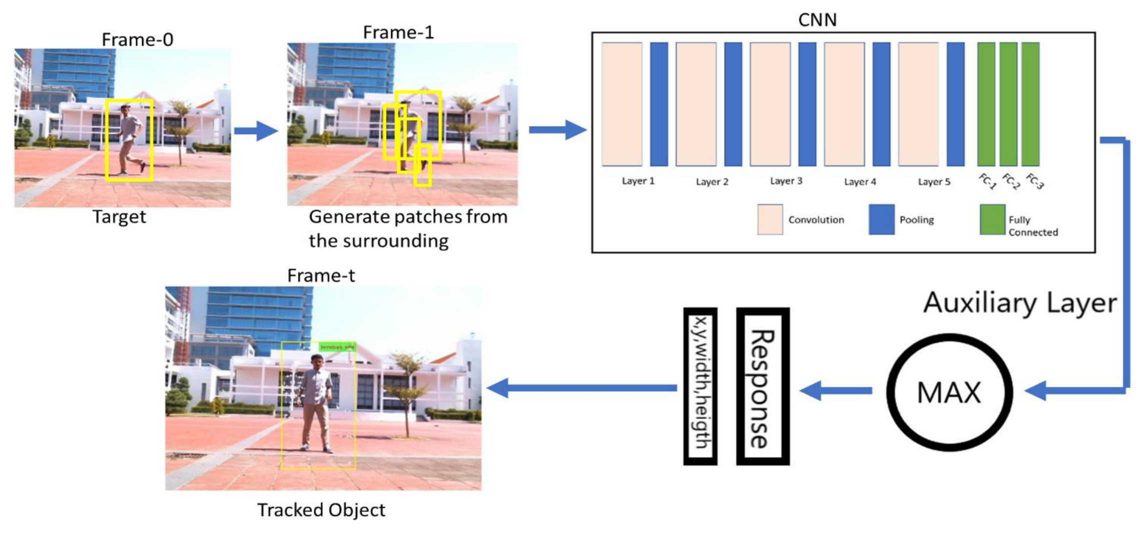
Design of Convolutional Neural Networks

TABLE I. ARCHITECTURE OF CNN

Layer	Type	Input Size	Kernel Size	Feature Map
1	Convolution	224x224x3	11x11x3x96	96
	Relu	55x55x96	-	96
	Pooling	55x55x96	3x3	96
	Normalization	55x55x96	5x5	96
1*	Weight aux layer	55x55x96	55x55x96	96
2	Convolution	55x55x96	5x5x96x256	256
	Relu	27x27x256	-	256
	Pooling	27x27x256	3x3	256
	Normalization	27x27x256	5x5	256
2*	Weight aux layer	27x27x256	27x27x256	256
3	Convolution	27x27x256	3x3x256x384	384
	Relu	13x13x384	-	384
4	Convolution	13x13x384	3x3x384x384	384
	Relu	13x13x384	-	384
5	Convolution	13x13x384	3x3x384x256	256
	Relu	13x13x256	-	256
	Pooling	13x13x256	3x3	256
6	Fully Connected	13x13x256	-	4096
7	Fully Connected	4096	-	4096
8	Fully Connected	4096	-	4096
9	Fully Connected	4096	-	2



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Design of Convolutional Neural Networks

In the design of the CNN architecture that we created, using a 224 x 224 x 3 channel image from the RGB image that was used as input for CNN. At the convolution layer on each different layer, we also use different kernel sizes according to the layer of CaffeNet used in this research. There are a total of 5 layers of convolution as well as non-linearity to maximize extraction of information from images. At layer 1 and layer two we add a layer, the auxiliary layer that is used for the tunning weight from deeper images. Besides that, in the fully connected layer, we deleted all the parts that were the original versions of this architecture, and then we replaced it with the new fully connected three layers. This layer consists of 4096 nodes. At the end of the fully connected layer, it is connected directly to an output layer consisting of 2 nodes to classify targets or not targets.. With this, we save several hours from training a complete network.

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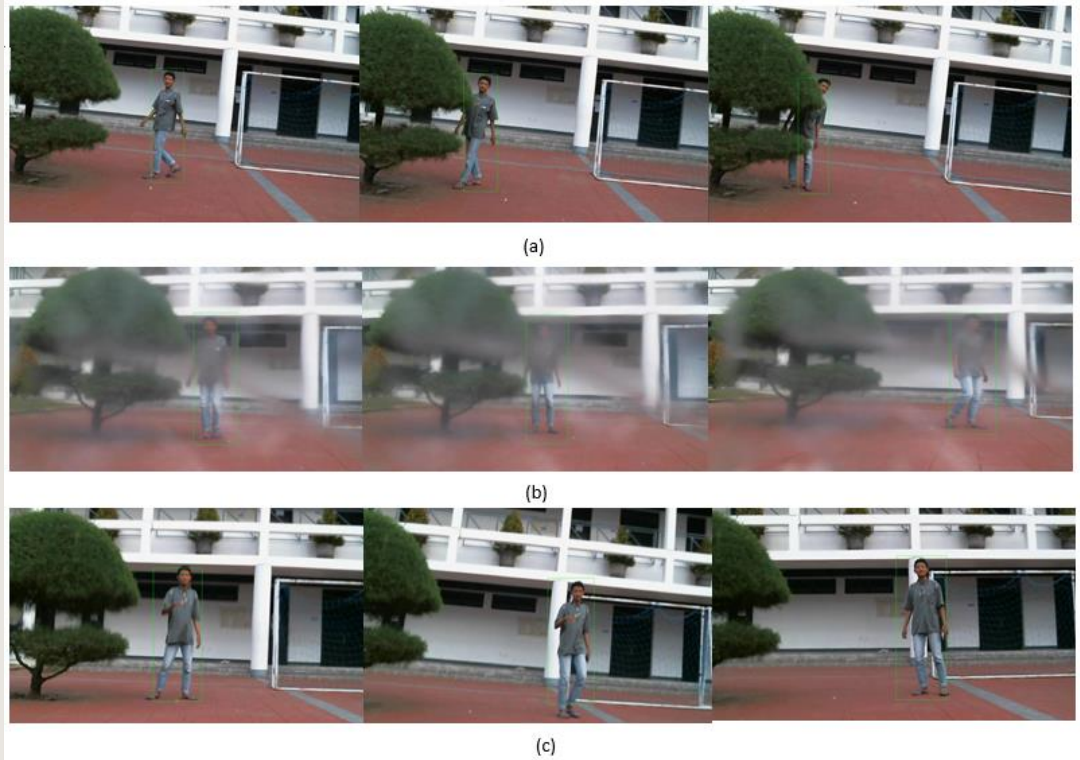
Result of Convolutional Neural Networks

Based on Figure, we could see that CNN can provide optimal results for human detection by being able to detect in various circumstances such as objects blocked by other objects, blurry images and vibrating images. These results give great hope in research in military technology developments that in the end, the method of detecting these targets will be able to detect targets in various environments and be able to distinguish the ID from that target.



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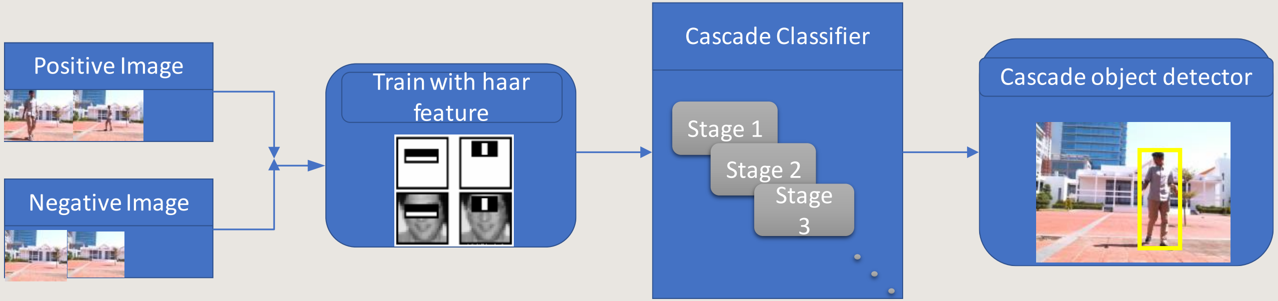
Design of Haar Cascade Classifier



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Design of Haar Cascade Classifier

Cascade classifier detects objects as quickly as possible in each stage, rejecting the negative label on the image. With assumptions made that there is nothing at all in the region that needs to be processed or an object that is verified. However, on a positive label, it will take much time to verify the image. When classifier detects the right detection, it is a true positive. When the classifier detects negative label as positive, it is a false-positive.

The overall false positive rate of the cascade classifier is f s , where f is the false positive rate per stage in the range (0 1), and s is the number of stages. Similarly, the overall true positive rate is t s , where t is the true positive rate per stage in the range (0 1). Thus, adding more stages reduces the overall false-positive rate, but it also reduces the overall true positive rate.

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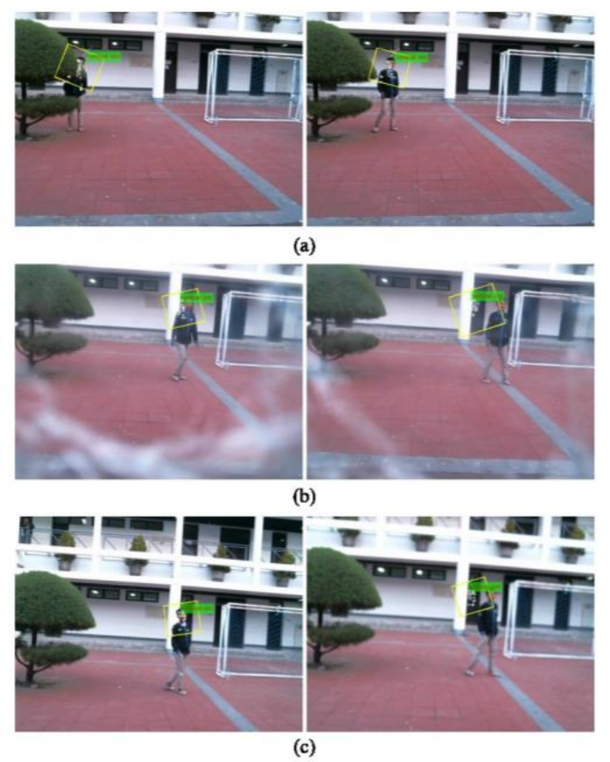
Result of Haar Cascade Classifier

Based on Figure, we know that using the Haar cascade classifier could detect hidden objects because they are blocked by other objects with only a portion of the body visible to the camera. While for blur and vibrating images, this method has not shown the results of optimal detection. There is still much false-positive detection that occurs in experiments carried out. In addition to causing less accurate detection, complex background environments also make the feature extraction process carried out by cascade also longer. Finally, the object detection done by the gun turret is less optimal because the frame rate becomes slower.



(a) (b) (c)

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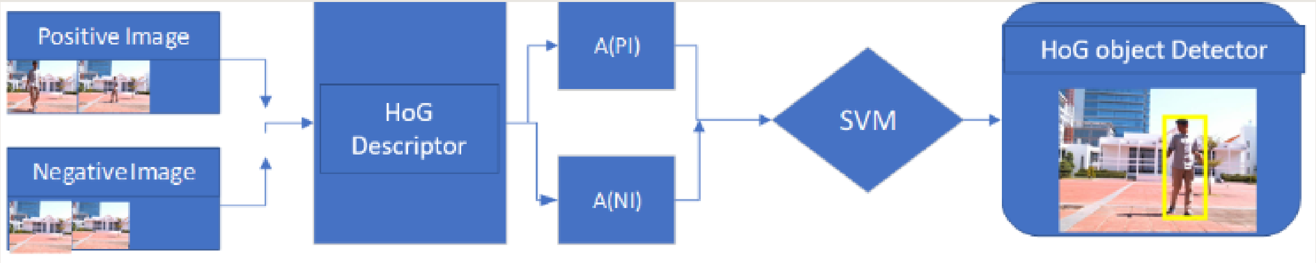
Design of HOG with SVM Classifier



Similar to Haar cascade classifier, HOG with SVM classifier detects labels from images including positive images or negative images. Positive images (P) and negative images (N) will then be processed using HOG Descriptors. By using gradient value information from the local region, the value is then used as a cell histogram. The information presented by this cell histogram is then reinforced by the normalization function.

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Design of HOG with SVM Classifier

From this process, the HOG descriptor occurs. We train a linear SVM on our positive and negative samples. In the set of feature descriptors (64 x 128 x 3 = 3780 values) is used to feed the SVM classifier, which generates a model (a set of support arrays). SVM will then generate a model of the training that has been done. During the classification process, the descriptor calculates the similarity of the values entered. Classification, decision making, and clustering are directly carried out by SVM. Moreover, in this study using a linear kernel to classify descriptors from data that has been trained.

If the classifier detects an empty image to be defined as an object, obviously this is false positive, and this is an error that often occurs in detecting objects using HOG. Therefore, to overcome this, record the vector feature of the image, then compare it with the value of false-positive by using the probability of classification. This process is called hardnegative mining. This process also adds to the burden of the classification process, but to minimize detection errors, this needs to be done.

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Result of HOG with SVM Classifier

Based on Figure, we know that using the HOG method with SVM classifier can detect hidden objects because they are blocked by other objects with only a portion of the body visible to the camera. While for blur and vibrating images, this method has not shown the results of optimal detection. There is still a lot of false-positive detection that occurs in experiments carried out. In addition to causing less accurate detection, complex background environments also make the feature extraction process carried out by HOGs also longer. Finally, the object detection done by turret gun is less optimal because the frame rate becomes slower.

(a) (b) (c)

CONCLUSION

From the research that has been done, it can be concluded that Machine Learning with Deep Learning features such as Convolutional Neural Network has more robustness for hiding objects, blur images and vibrating images then Shallow Learning features such as Haar-Cascade Classifier and Hough Transform with SVM Classifier. In addition, CNN also has better detection accuracy so that tracking objects has more accurate movements with the position of objects that are always close to the center position of the camera.

LINK VIDEO

https://youtu.be/_sq6_c9lq7Y

THANKS!