

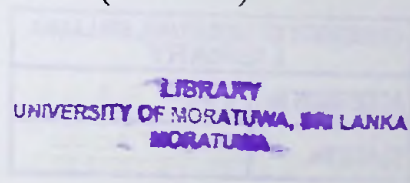
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REAL-TIME HUMAN DETECTION ANALYTICS IN CONSTRAINED IMAGE INPUTS

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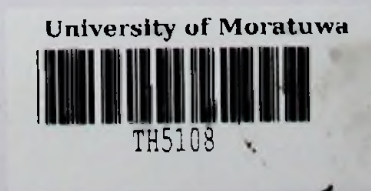
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DECLARATION

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ABSTRACT

Real-time video surveillance is a growing trend today. Our surrounding is being monitored daily by an increasing number of surveillance camera systems. Analyzing human movement can be used for the wellbeing of humans. There are a set of analytical tools and algorithms which can be used to detect, track, and analyze humans in images. Human movement analytics has various subdomains including human detection, human recognition, human tracking, human localization, human reidentification, human behavior analysis, and abnormal activity detection. Human detection is the most crucial step among them, and which helps to derive other sub domains.

Human detection analytics in constrained lighting conditions would be a challenging task to apply due to the low contrast of the image context. Currently available systems focused on the daytime. The background light is an essential factor in the camera images, which rigorously affects the quality of the image. We can identify considerable differences if we compare two images at the rich light condition and constrained light condition. Fewer features of the objects can be extracted in constrained light conditions than rich light conditions. Illumination of the background context is an important factor if we focus on such applications. Currently, most researchers have used human detection analytics in visible light. RGB image shows a clear view when there is sufficient light existing, and it is highly sensitive to visible light conditions compared to infrared. In this research, we considered infrared images as constrained image inputs.

Our proposed methodology contains a novel human detection approach based on machine learning and a motion dynamic model. Here we have addressed the problem using a combination of Deep Convolutional Neural Networks (DCNN) for human detection and Kernelized Correlation Filters (KCF) for human tracking. MobileNet pre-trained model is used for frame-wise human detection as the first step. Then the KCF object tracking algorithm is used to increase the human detection accuracy while tracking the human in the context. Furthermore, we applied some preprocessing techniques to reduce the noise effects. Currently, the progress made by this research-based project is sufficient to initiate the development of a complete human detection analysis solution based on live CCTV camera footage. This solution provides the core functionality of human detection analytics and it can be easily adapted to different domain solutions such as customer behavior analytics in a supermarket or worker movement analytics in an industrial premise.

Keywords: Human Detection, Human Tracking, Deep Neural Networks, MobileNet, Kernelized Correlation Filters, Infrared, Realtime Video Feed, Histogram Equalization

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LIST OF ABBREVIATIONS

Abbreviation	Description
DCNN	Deep Convolution Neural Network
IP	Internet Protocol
KCF	Kernelized Correlation Filters
CCD	Charge Coupled Device
HOG	Histograms of Oriented Gradients
SVM	Support Vector Machine
FLIR	Forward Looking Infrared
YOLO	You Only Look Once
ABMS	Adaptive Boolean Map based Saliency
BMS	Boolean Map based Saliency
SCA	Stel Component Analysis
CWBTFs	Cumulative Weighted Brightness Transfer Functions
IR	Infrared
SAD	Sum of Absolute Differences
SIFT	Scale Invariant Feature Transform
SURF	Speeded Up Robust Feature
LBP	Local Binary Pattern
RoI	Region of Interest
MIL	Multiple Instance Learning
IoU	Intersection over Union
FLIR	Forward Looking Infrared