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Unusual Human Activity Detection

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Abstract – Suspicious behavior is dangerous in public and can cause serious causality. There are various systems developed based on the capture of video images with motion and pedestrian detection, but these systems are not intelligent enough to detect anomalous activity even in real time. Escape from video surveillance needs to be detected in real time in order to manage casualties quickly and quickly before they occur. The proposed system focuses on the detection of suspicious activity and aims to realize a technique that can automatically detect suspicious activity using computer vision. Here, the system uses the OpenCV library to classify different types of actions in real time. Motion influence maps were used to represent motion analysis that frequently repositions from one location to another. The system uses pixel-level representations to facilitate understanding or identification of the actual situation

Key Words: *Pedestrian, surveillance, OpenCV, Motion influence maps.*

1. INTRODUCTION

Detecting human activity is a wonderful task advancing into a connected era. Universally accessible sensors and wearables, also known as the Internet of Things (IoT). At the heart of supportive innovation is information about what happens when a client tries to understand his or her behavior. By leveraging unlisted information, professionals and countless customers can become smarter, get more information about grouping actions, and benefit from understanding the machines around them. I can do it. Much research has been done in the field of human activity recognition (HAR) to distinguish normal activities in daily life (walking, running, sitting, standing, etc.). Accounts are proposed for a variety of features and activities that have a more algorithmically complex structure. Analysis was done on what happened at irregular intervals and could occur in other activities. The motivation for behavior recognition is to identify the efforts and goals of at least one operator from a series of statements about expert elements and natural conditions. Since the 1980s, exploration in this area has attracted the attention of many software engineering networks due to its diverse nature, providing individualized help in a variety of applications and areas, such as recovery, human-PC communication, etc. I am. Or humanism, references to actions in different regions, may be referred to as plan confirmation, goal confirmation, goal confirmation,execution confirmation, regional estimation and regional management.

Figure 1.Group Activity Detection

Figure 1 shows group activity that can be tracked through either a physical sensor network or computer vision. Sensors are less capable of accurately capturing actions detected in groups, rather than computer vision being an effective approach to doing the same. The Movement Impact Map is a movement mapping technique that separates vitality at this point. Exercise impact map developed from these energies. Motion Impact Maps can adjust the highlights and contrasts of motion impact to detect anomalous human behavioral positions.

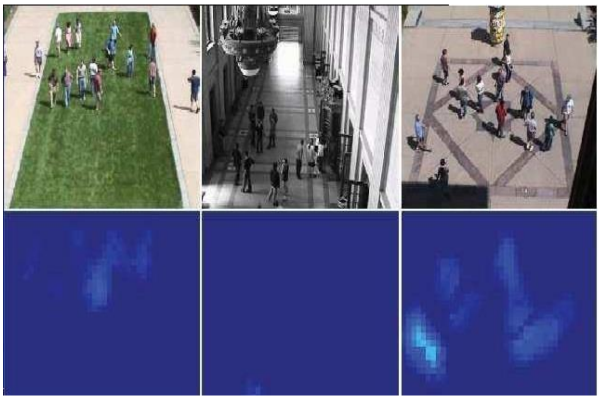


Figure. 2.Usual Motion Influence Map

As shown in Figure 2, the movement is normal or normal and does not change frequently between frames at a particular time interval of You can see that there is no effect on the map. Frequent changes will show the impact on the map, as shown in Figure 3.

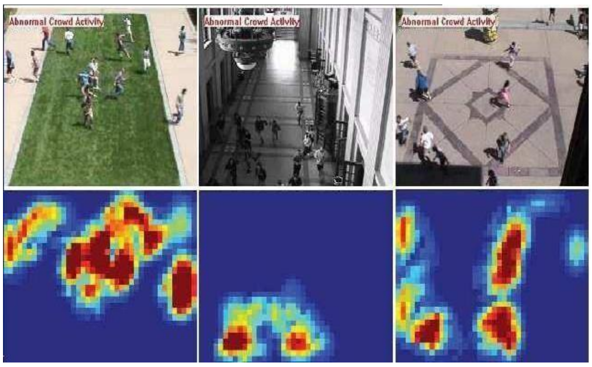


Figure 3. Unusual Motion Influence Map

2. RELATED WORK

Suspicious training and individual security in the open zone are under real threat. Numerous video reconnaissance frames are used in open areas such as roads, detention centers, privileged areas, air terminals, and grocery stores. Video reconnaissance cameras aren't smart enough to pick up irregular drills during ongoing operations. It is important to verify the detection of suspicious exercises and the legitimacy of the reconnaissance video. For quick and quick management, you need to consider the rush situation perceived by continuous video surveillance.

Zakia Hammaletal. [4] proposed a framework based on traditional neural networks that trains human face recognition. Prepare the frame w.r.t. Articulation to be blamed. CNN-based AU sites have revealed equivalent changes in discoveries regarding newborn quality between missions. The correct answer rate for recognition or articulation rights is 79-93%.

He Xuetal. [5] proposed a framework based on RFID, which is a physical sensor.

The RFID framework can be separated into three segments: reader, tag, and backend PC framework. It can be sent via the par user and the tag's receive wire. The means of establishment by the RFID framework are as follows. (1) The par user sends a wireless repeat flag in a comprehensive state and checks whether the tag exists. (2) A tag within the read range of the user's receiving device is activated by its own receiving line to communicate with the user and send the user's electronic chip code or other information. (3) The RFID reader acquires the information mark of the electronic item code (EPC) or tag via the receiving device. The information is then decoded and processed and sent to the back-end PC framework.

Varsha Shrirang Nanaware et al. [6] outlines the various frameworks implemented for activity verification. Various experts point out in undeniable

-hour travel videos the locating procedures and confirmation of activities of different human activities. Through this vibrant and negative application of useful research areas, a comprehensive overview of the work in progress by various authors is provided. To be honest, the research / audit paper is prepared by the United States. This can be a starting point for investigating "various human activity tracking systems and activity detections in undeniably time-consuming video surveillance."

Jiahao Lietal. [7] proposed a framework that relies on a pyramid-type vitality map as a highlight descriptor for enclosure grouping. It can store and represent a history of spatially contrasting activities and perceived activities. It relies on a bidirectional neural system that can trace the hidden layers and present the most relevant results. Equally powerful against a single target or skeleton, but fails against different targets.

Nour El Din Elmadanyetal. [8] proposed a framework that relies on Biset Globality Locality Preserved Canonical Correlation Analysis. This means familiarizing yourself with the normal component subspace between the two sets.

The next strategy is a multi-set global locality-conserving canonical correlation analysis that expects to maintain at least three sets. Create an array of skeletons as an index of information. The accuracy of the correct confirmation rate is 90.1%. Soumalya Senetal. [9] proposed a framework that relies on image analysis procedures. Image analysis refers to the different types of human-performed activities that can be recognized by a group of enclosures. Activities are organized as follows: walking, running, applauding, running, biking, surfing, etc. Which scaffold improves more detailed inspection and saves these edges for future correlation depends on the connection between the front and the foundation. Image analysis integrates image segmentation, object detection or verification.

3. PROBLEM IDENTIFICATION

Although various studies have been conducted in the field of human activity detection, few studies have been found to detect abnormal human activity in real time using a camera. Computer vision is an advanced approach that can capture human activity in real time. The previously proposed system can use skeletal recognition to recognize individual user behavior, especially in the category of human activity. This type of action can only be detected in simple backgrounds, not in non-simple backgrounds or outdoor scenes. This system cannot recognize multi-user actions, making it difficult for the system to recognize group or crowd-based activities. The system is designed to detect human activity from crows, detect anomalous activity, and receive advance notice to help heal large victims. Skeleton tracking works at certain angles or distances, but it is not useful at high altitudes due to inaccurate accuracy.

Suspicious training and individual security in the open zone are under real threat. Numerous video reconnaissance frames are used in open areas such as roads, detention centers, privileged areas, air terminals, and grocery stores. Video reconnaissance cameras aren't smart enough to pick up irregular drills during ongoing operations. It is important to verify the detection of suspicious exercises and the legitimacy of the reconnaissance video. For quick and quick management, you need to consider the rush situation perceived by continuous video surveillance. Zakia Hammaletal. [4] proposed a framework based on traditional neural networks that trains human face recognition. Prepare the frame w.r.t. Articulation to be blamed. CNN-based AU sites have revealed equivalent changes in discoveries regarding newborn quality between missions. The correct answer rate for recognition or articulation rights is 79-93%.

Figure 4. Skeleton Recognition for Single User Activity Detection [10]

3. PROPOSED WORK & IMPLEMENTATION

The proposed work can detect human activity in a crowd of and analyze whether its behavior is general or abnormal. The system discusses purely with crowd-based activities that ensure the situation. The system uses the OpenCV library with a Python IDE that works with the highest precision. The system proposes a motion impact map with the correct detection rate. The proposed framework focuses on detecting suspicious movements and se eks to find a way to naturally detect suspicious actions using a PC vision strategy. The proposed system uses motion influence maps that show frequent changes in frames at short time intervals to classify differences between frames. Detecting anomalous crowd activity can be a daunting task, especially for sensor networks. Computer vision is an effective approach that allows you to capture human activity in real time and analyze anomalous frames later. More specifically than, you must first enter a crowd video that contains both common and unusual activity through the flow chart. When the input makes a frame selection, it starts and the total number of frames is also validated. The process ends when the current frame reaches the last frame. Otherwise, it will continue to detect anomalous activity. Hj calculates how much the feature affected the map that was tracking the feature vector. The extracted feature is the influence density of the motion influence map. Depending on the anomalous density required to declare anomalous activity, it will only affect the map if it is greater than the threshold density. If it is greater than the threshold, the decision is declared as anomalous activity. Otherwise, no unusual activity was detected.

Figure 5. Crowd Stampede Scene [11]

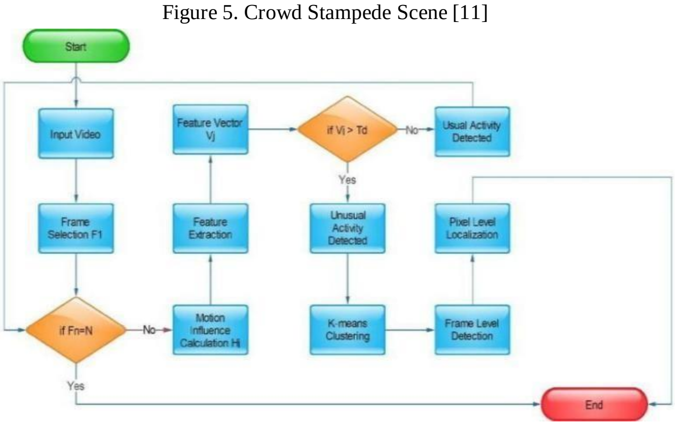
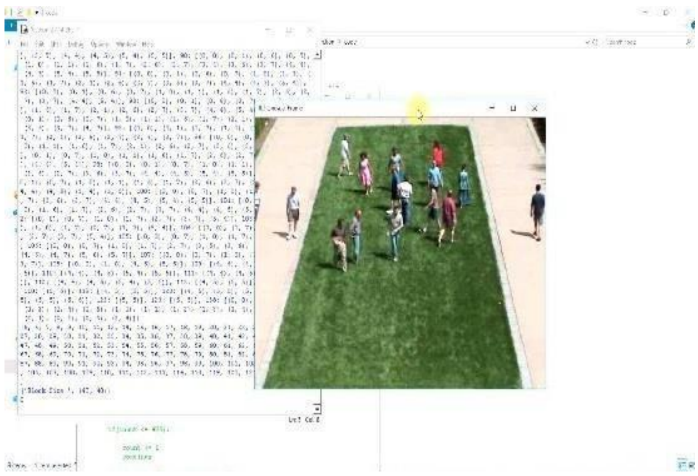


Figure 6. Flow Chart

The proposed work can detect human activity in a crowd of and analyze whether **their** behavior is general or abnormal. The system **talks** purely with crowd-based activities that **guarantee** the situation. The system uses the OpenCV library with a Python IDE that works with the highest precision. The system proposes a motion impact map with the correct detection rate. The proposed framework focuses on detecting suspicious movements and seeks to find a way to naturally detect suspicious actions using a PC vision strategy. The proposed system uses **a** motion **impact map** that **shows** frequent changes in frames at short time intervals to classify differences between frames. Detecting **an unusually large amount of** activity can be a daunting task, especially for sensor networks. Computer vision is an effective approach that allows you to capture human activity in real time and analyze anomalous frames later. More **specifically, rather** than**,** you **should** first enter a crowd video that contains both **general** and unusual activity through the **flowchart.** When the input **hits the** frame selection, **the input is started** and the total number of frames is also validated. The process ends when the current frame reaches the last frame. Otherwise, it will continue to detect anomalous activity. Hj calculates how much the feature affected the map that was **tracing** the feature vector. The extracted feature is the influence density of the motion influence **map.**

Figure 7. Usual Activity Detection



A. Motion vector algorithm

What you need: S ← block size, K ← set of blocks in frame, B ← motion vector set, M ← motion impact map, I ← moving object, D (i, j) ← Euclidean Distance Between object i and block j, Td is the threshold, φij ← the angle between the vectors from object i to object j.

Input: B ← Motion vector theorem.

OUTPUT: H ← Motion Influence Map.

Step 1: Hj (j ∈ K) is set to zero at the beginning of eachframe

Step 2: for all i ∈ K doTd = ‖

bi ‖ × S;

$\frac{Fi}{2} = \angle b_i + \frac{\pi}{2}$;$-\frac{Fi}{2} = \angle b_i$

$- \frac{\pi}{2}$ *;for all j ∈ K do*

if i ≠ j then

Calculate the Euclidean distance D(i, j) between bi andbj

if D(i, j) < Td then

Calculate the angle φij between bi and bjIf $-\frac{Fi}{2}$

$< \varphi_{ij} < \frac{Fi}{2}$ *then*

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$$H^j(\angle b_i) = H^j(\angle b_i) + exp\left(-\frac{D(i,j)}{\| bi \|}\right)$$

end ifend if

end ifend

for

end for

Step 3: H^j with respect to $\angle$ b_i is reflected motion influence map

Indicate motion influence vector V_jStep

4: End

B is the input as a motion vector set and H is output as a motion impact map that needs to be investigated. In step 1, set Hj to zero at the beginning of each frame. Hj is the effect of motion on the j block. Where j belongs to K, which is a set of blocks in the frame. In step 2, the "for" condition must be applied. Where i is the position that belongs to K in the set of blocks. Calculate a threshold Td equal to twice the mod of bi and multiply it by the block size S. Since the frame from the origin has two directions, Fi / 2 and Fi / 2, the angle must be calculated according to the following directions. Motion vector. You need to calculate the Euclidean distance between both the origin and the position of the motion vector. When the calculation is complete, it is verified if it is less than the threshold and the angle between bi and bj is calculated. This is the angle between the origin and the motion vector. Next, we need to find out in which direction it is heading. If you're happy with it, you'll eventually use the vector position to calculate the motion impact weights and later place them in a pixel or frame-level display. However, there are specific steps to localize the effects of movement.

In motion effect maps, squares with strange actions have their own motion effect vector along with adjacent squares. Separately, when the action is intercepted by several consecutive housings, it ejects an element vector from Cubeid characterized by n × n obstacles on the last T edges. The megablock is the sum of the speed effect values of all the smaller blocks that make up the larger block.

Extraction Features Recently, the number of "t" frames is divided into megablocks, and for each megablock, a short feature vector of 8 × t dimensions is drawn in every frame. For example, enclose a megablock (the "T" number of "t" in a frame) and their feature vectors to create a unique feature vector for block (1,1). For each grouping of Super Squares, combine spatiotemporal highlights and set the focus as a codeword. This is the explanation. (I, j) For Ubersquare, the K codeword {w (i, j) k} k = 1. Now you need to keep this in mind in a regular exercise with a preparatory cut.

Therefore, the Uber Square codeway is an example of a typical drill that could be in each zone. Minimal separation grid test creates a basic separation grid e on overconstrained, where the estimation of the components between features is not exactly Euclidean, after excluding the spatial grammar error highlighting vectors of all supersquares. .. The super square associated with the current test design is identified by the vector code. Introducing amazing edge-level exercises into the base separation grid lowers component estimates and reduces the likelihood of anomalous actions in the associated squares.

Computer Vision is currently being further developed using OpenCV with Python. The Python IDE is a platform where some image processing concepts are calculated with high precision. The configuration is very easy to install in Python, several packages are available and can be used from anywhere in the country. OpenCV is an advanced computer vision library that helps you calculate the effectiveness of machine vision. Motion influence maps are easy to draw in Python, and pixel-level representations are often easy. Motion influence requires several Python packages to run effectively with a high level of true detection accuracy. Python also makes it easy to code and test at the same time by taking a test-driven development (TDD) approach. There are huge libraries for Python and OpenCV that allow users to implement their system with less code. Most smartphone applications are developed in Python, which interacts intelligently with humans.

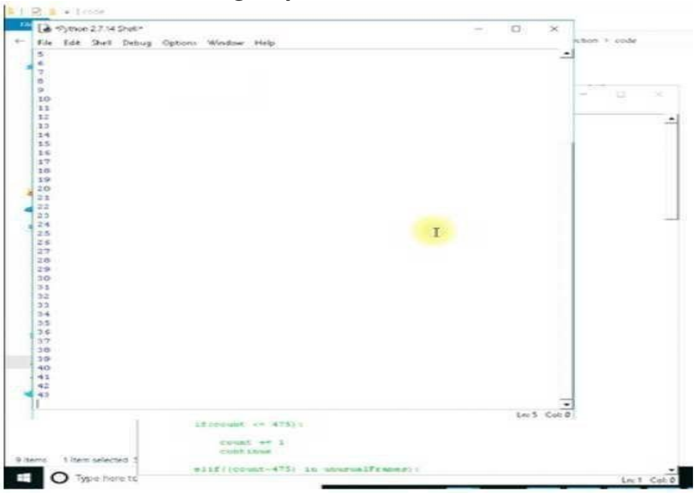
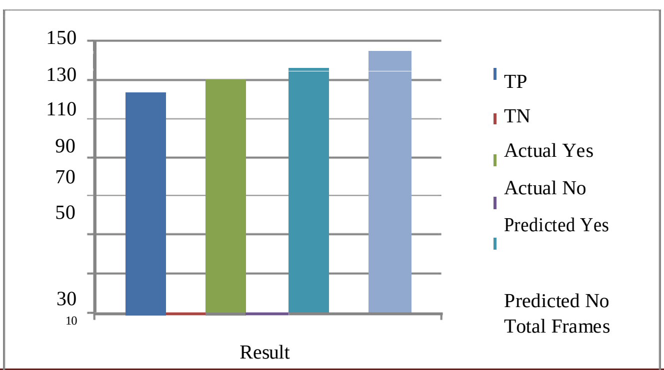


Figure 8. Frame Analysis in Python IDE

4. RESULT ANALYSIS

Results were analyzed based on true positives, true negatives, real yes, real no, predicted yes, and predicted no. There are 147 in total. The number of frames. A true positive of 122 means that there is anomalous activity in the frame of 122 and a positive and a true negative of 20 are detected, which means a true rejection. The system contains normal or unusual ones, but the system denies its real existence. But the actual yes is 132 and the actual no is 15. Prediction is that 136 is yes and 11 is no. Based on this, the overall accuracy was calculated to be 96.59%, the accuracy was 89.70%, and the recognition value was 92.42%.

GRAPH I. RESULT ANALYSIS

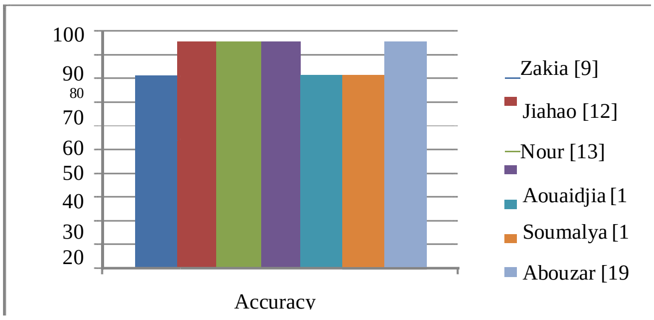


Graph 1 shows the results at the frame level, whether or not they contain anomalous activity. Results were calculated based on true positives, true negatives, real yes, real no, predicted yes, and predicted no. The number of frames received. These simulations were used to calculate precision, recall, and overall accuracy.

TABLE I. RESULT COMPARISON

	Accuracy %
Zakia Hammal [1]	84
Jiahao Li [4]	95.97
Nour El Din Elmadany [5]	94.14
Aouaidjia Kamel [6]	94.51
Soumalya Sen [7]	88.70

GRAPH II. RESULT COMPARISON



5.CONCLUSION

The systems proposed so far are designed to recognize simple human behaviors such as walking and running, but they are not suitable for crowded areas. The proposed system can detect anomalous human behavior from the crowd and act accordingly using motion influence maps and OpenCV. The accuracy rate is slightly higher than others, and this concept has not been studied much. The proposed system can function for security pre-assessment. The accuracy is 96.42%, which is enough to find anomalous activity in complex backgrounds. The proposed system can use OpenCV and motion influence maps to efficiently detect anomalous human activity in the crowd, greatly improving the accuracy and performance of the system. Abnormal crowd detection can be implemented in various public places for crime prediction and notification, improving accident management. However, accuracy is often important, and accuracy needs to be improved in order to develop an ideal system that can be implemented in practice.

REFERENCES

[1] Lee, H. Suk, S. Park and S. Lee, "Motion Influence Map for Unusual Human Activity Detection and Localization in Crowded Scenes," in IEEE Transactions on Circuits and Systems for VideoTechnology, vol. 25, no. 10, pp. 1612-1623, Oct. 2015.

[2] Donghui Song, "https://www.youtube.com/watch?v=y7Jo_9Z9z0U", Published on Jun 13, 2018.

[3] D. Lee, H. Suk, S. Park and S. Lee, "Motion Influence Map for Unusual Human Activity Detection and Localization in Crowded Scenes," in IEEE Transactions on Circuits and Systems for VideoTechnology, vol. 25, no. 10, pp. 1612-1623, Oct. 2015.

[4] Zakia Hammal1, Wen-Sheng Chu1, Jeffrey F. Cohn1,2, Carrie Heike3, and Matthew L. Speltz4, "Automatic Action Unit Detection in Infants Using Convolutional Neural Network", 2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII), IEEE.

[5] He Xu1,2, Chengcheng Yuan1, Peng Li1,2, Yizhuo Wang3, "Design and Implementation of Action Recognition System Based on RFID Sensor", 2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD 2017), IEEE.

[6] Mrs. Varsha Shrirang Nanaware, Dr. Mohan Harihar Nerkar and Dr. C.M. Patil, "A Review of the Detection Methodologies of Multiple Human Tracking & Action Recognition in a Real Time Video Surveillance", IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI- 2017).

[7] Jiahao Li†, Hejun Wu∗ and Xinrui Zhou‡, "PeMapNet: Action Recognition from Depth Videos Using Pyramid Energy Maps on Neural Networks", 2017 International Conference on Tools with Artificial Intelligence, IEEE.

[8] Nour El Din Elmadany, Yifeng He and Ling Guan, "Information Fusion for Human Action Recognition via Biset/Multiset Globality Locality Preserving Canonical Correlation Analysis", IEEE TRANSACTIONS ON IMAGE PROCESSING, 2018.

[9] Soumalya Sen, Moloy Dhar and Susrut Banerjee, "Implementation of Human Action Recognition using Image Parsing Techniques", 2018 Emerging Trends in Electronic Devices and Computational Techniques(EDCT), IEEE.

[10] Frontiersin,"https://www.frontiersin.org/files/Articles/160288/f robt-02-00028-HTML/image_m/frobt-02-00028-g008.jpg".

[11] Hqdefault, "https://hvss.eventsmart.com/events/intro-concealed-carry/hqdefault/".

[12] D. Aranki, G. Kurillo, P. Yan, D.M. Liebovitz, and R. Bajcsy, "Continuous, real-time, tele-monitoring of patients with chronic heart-failure: lessons learned from a pilot study," in International Conference on Body Area Networks (Bodynets), 2014.

[13] Abouzar Ghasemi and C.N. Ravi Kumar, "A Novel Algorithm To Predict And Detect Suspicious Behaviors Of People At Public Areas For Surveillave Cameras" Proceedings of the International Conference on Intelligent Sustainable Systems (ICISS 2017)

[14] Y. Nam, S. Rho, and J. Park, "G3d: A gaming action dataset and real time action recognition evaluation framework," IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2012.

[15] Y. Nam, S. Rho, and J. Park, "Intelligent video surveillance system: 3-tier context-aware surveillance system with metadata," Multimedia Tools and Applications, vol. 57, pp. 315–334, 2012.

[16] A. F. Bobick and J. W. Davis, "The recognition of human movement using temporal templates," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, pp. 257– 267, 2001.

[17] M. Blank, L. Gorelick, E. Shechtman, M. Irani, and R. Basri, "Actions as space-time shapes," 2005, pp. 1395–1402.

[18] I. Laptev and T. Lindeberg, "Local descriptors for spatio- temporal recognition," in Spatial Coherence for Visual Motion Analysis, 2006.

[19] X. Yang, C. Zhang, and Y. Tian, "Recognizing actions using depth motion maps-based histograms of oriented gradients," in ACM International Conference on Multimedia (MM), 2012.

[20] J. Wang, Z. Liu, J. Chorowski, Z. Chen, and Y.Wu, "Robust 3d action recognition with random occupancy patterns," in European Conference on Computer Vision(ECCV), 2012.

[21] X. Yang and Y. Tian, "Eigenjoints-based action recognition using navebayes- nearest-neighbor," in IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, 2012.

[22] M. Gowayyed, M. Torki, M. Hussein, and M. El-Saban, "Histogram of oriented displacements (hod): Describing trajectories of human joints for action recognition," in International Joint Conference on Artificial Intelligence (IJCAI), 2013.