ITU KALEIDOSCOPE
SANTA FE 2018

Machine learning for a 5G future

Optical Flow Based Learning Approach For Abnormal Crowd Activity Detection With Motion Descriptor Map

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Outline

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- Direction & Influence Weight in Motion Descriptor
- Motion Descriptor Pattern Clustering and Nearest Neighbor Search
- Algorithm Development
- Performance Evaluation
- Acknowledgement

Overview

- Development of Intelligent visual surveillance (IVS) for identification of specific objects, behaviors or attributes in video signals
- The IVS system transforms the video signals into structured data
- Monitor and analyses user activity and behavior at the application level

ITU-T recommendation F.743.1 – "Requirements for intelligent visual surveillance"

ITU-T recommendation X.1157 – "Technical capabilities of fraud detection and response for services with high assurance level requirements"

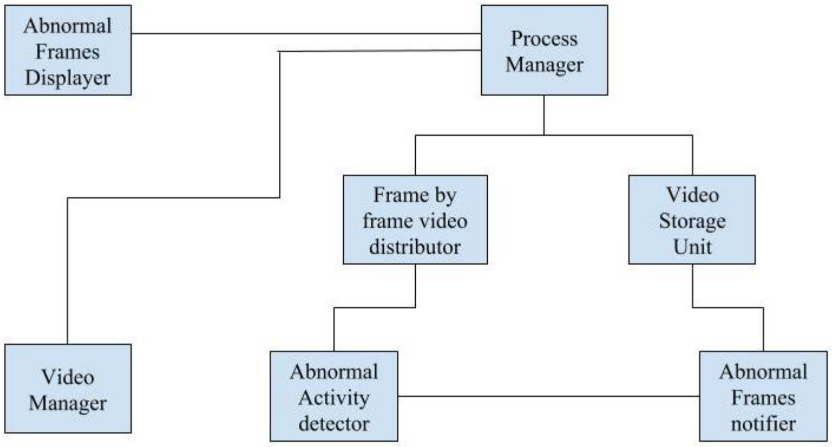

Fig. Functional components of the abnormal activity detection system

Proposed System Model

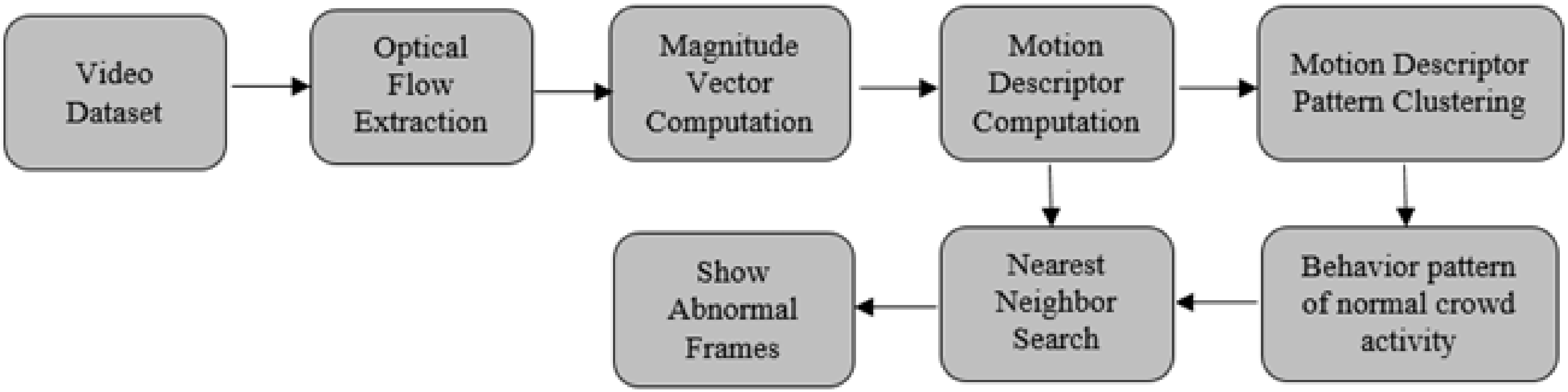

Fig. Overview of the proposed model for abnormal crowd activity detection

Magnitude Vector & Motion Descriptor

Magnitude Vector Computation

The magnitude of the block $\boldsymbol{b_i^k}$ in direction $\boldsymbol{k}$ is calculated as,

$$b_i^k = \sum_{p_d = k.\pi/4}^{(k+1).\pi/4} p_m$$

where $\boldsymbol{p_d}$ represents direction of motion of a particle and $\boldsymbol{p_m}$ represents magnitude of the particle.

Motion Descriptor Computation

Threshold $\boldsymbol{th_{b_i}}$ is computed as,

$$th_{b_i} = max(b_i^k).size_{b_i}$$

The flag variable $\boldsymbol{f}$ is computed as,

$$f = \begin{cases} 0\,, if\ ed_{ij} > th_{b_i} \\ 1\,, otherwise \end{cases}$$

Direction & Influence Weight in Motion Descriptor

The direction ***k*** of optical flow is assigned based on angle of deviation ($\boldsymbol{\theta}$) between block ***i*** and ***j*** as

$$k = \lfloor \theta \ / \ 45 \rfloor$$

Now, influence weight of block-*i* on block-*j*, $\boldsymbol{w_{ij}}$ is computed as,

$$w_{ij} \ = \ f.exp(-ed_{ij} \ / \ b_i^k)$$

Influence weight, $\boldsymbol{w_{ij}}$ of blocks is calculated for every frame in the video and added with influence weight of previous blocks called Motion Descriptor.

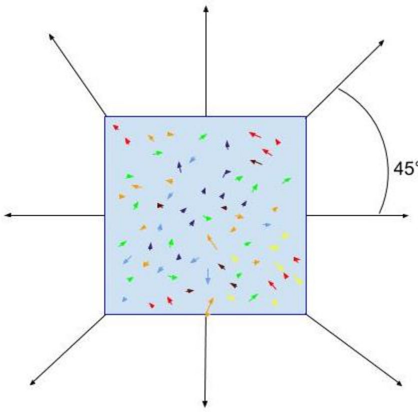

Fig. 1 - Visualization of a block with optical flow movements inside the block

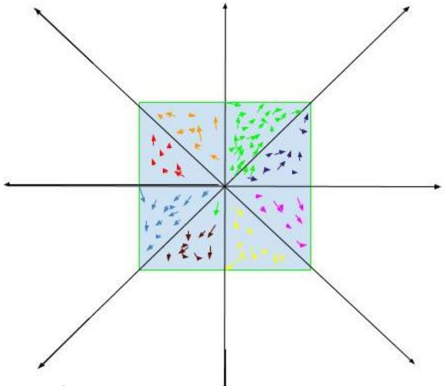

Fig. 2 - Classification of Optical Flow movements inside a block based on direction of movement

Motion Descriptor Pattern Clustering and Nearest Neighbor Search

The **motion influence vector** of the *j-th* block within a frame

$$M^{j}_{orien(b_i)} = \sum_{j} w_{ij}$$

Nearest Neighbor Search:
Minimum distance, $\boldsymbol{m_d}$ of deviation of the computed motion descriptor is calculated as,

$$m_d = \forall_c \min(eucl(c))$$

The block is considered abnormal if $\boldsymbol{m_d}$ is greater than the threshold of acceptance.

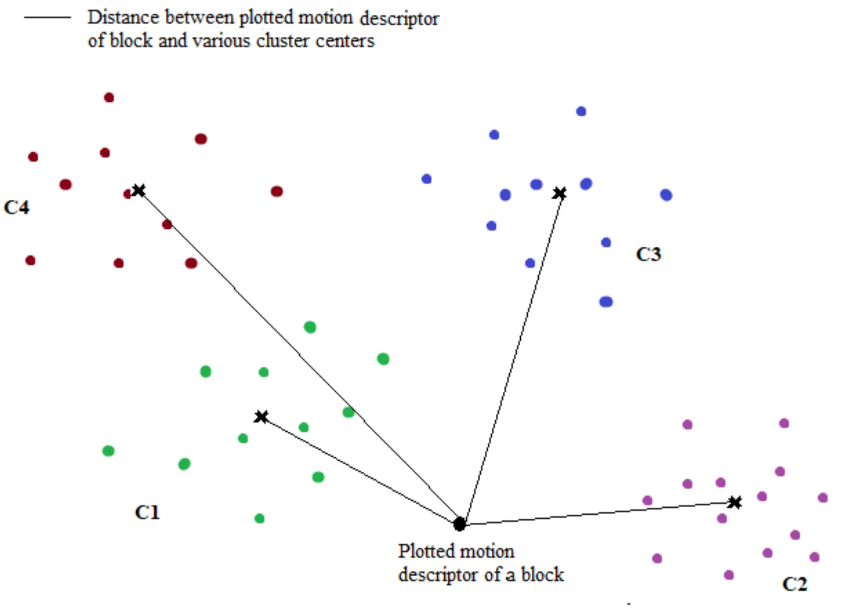

Fig. Visualization of detection of abnormal block in nearest neighbor search

Algorithm Development for Motion Descriptor Map

Input: K – Set of blocks in the frame

Output: M –Motion Descriptor Map

M is set to zero at the beginning of each frame

For all i in K

th_{b_i}= max(b_i^k).sizeb_i

For all $j \epsilon K$ where $j \neq i$

Compute ed_{ij} - Euclidean Distance between block i and j

if $ed_{ij} \leq th_{b_i}$

Compute direction (k_{ij}), weight (w_{ij}), *and* orientation ($M^j_{orien_{b_i}}$)

k_{ij} = $\lfloor \theta_{ij}$ / 45$\rfloor$ // Angle (θ_{ij}) between block i and j

w_{ij} = exp(-ed_{ij} / b_i^k)

$M^j_{orien_{b_i}}$ = $M^j_{orien_{b_i}}$ + w_{ij}

end if

end for

end for

Datasets for Performance Evaluation

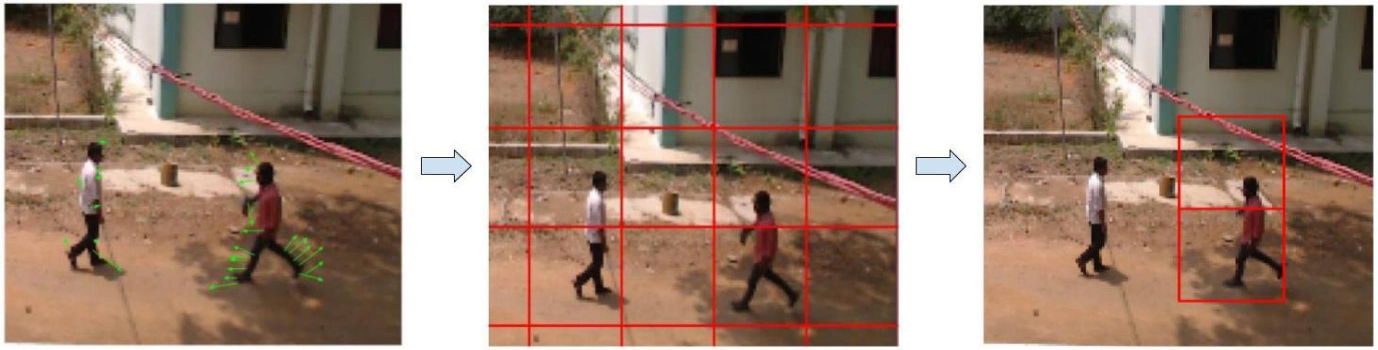

Figure 1 - Abnormal Crowd Activity detection with locally created dataset

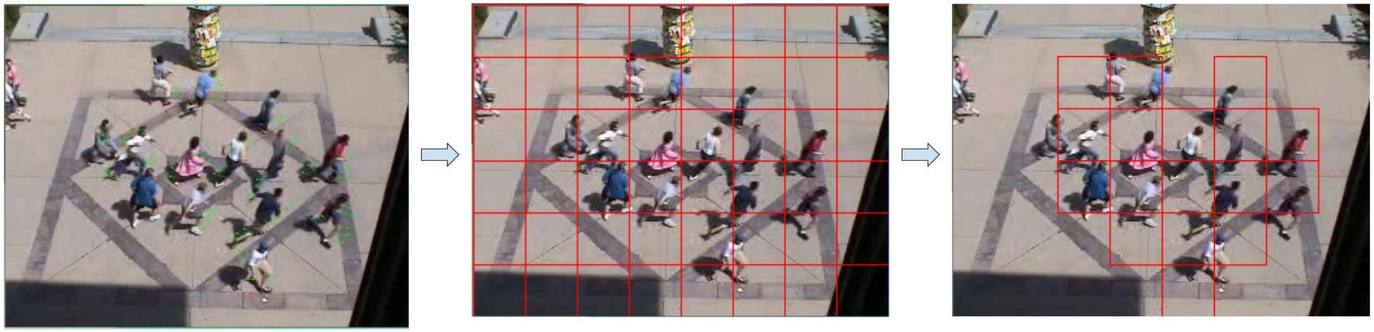

Figure 2 - Abnormal Crowd Activity detection with UMN dataset

Performance of the System

Table 1 – Effects of threshold values in UMN Dataset

Threshold of Acceptance	Performance		
	Accuracy	Recall	Precision
5.8368e-06	82.10	83.69	97.46
8.8292e-05	91.57	91.76	98.73
4.8368e-04	98.94	98.68	100
1.6586e-03	89.47	100	87.34

Table 2 – Effects of number of clusters in UMN Dataset

No of Clusters	Performance		
	Accuracy	Recall	Precision
4	98.94	98.68	100
5	98.17	98.66	98.66
6	98.94	100	92.73
7	98.78	98.68	96.10

Performance of the System cont.

Table 3 – Effects of block division of frames in UMN Dataset

Frame Division	Performance		
	Accuracy	Recall	Precision
8×6	98.94	98.68	100
10×8	96.35	97.20	99.25

Table 4 – Block level accuracy

Method	Datasets			
	UMN	UCSD		Created Dataset
		Ped 1	Ped 2	
HOFME [12]	98.52	72.70	87.50	95.04
Proposed Method	98.94	71.32	88.13	98.78

Table 5 – Frame level accuracy

Method	Datasets			
	UMN	UCSD		Created Dataset
		Ped 1	Ped 2	
HOFME [12]	84.94	86.30	89.50	93.56
Proposed Method	92.35	81.20	91.10	95.60

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Thank you

Acknowledgements

Anna University, Chennai, India