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Crashing Detection Module

Vif Descriptor

Report to explain the approach we took to make a crashing detection Module

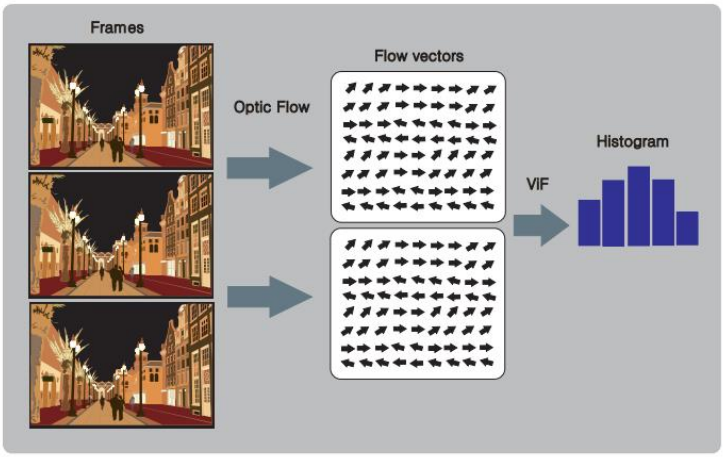
Introduction

We need a way to describe the flow of the scene to detect anomaly in the flows that could be caused by crashing.

We here consider how flow vector magnitudes change over time for short frame sequences, are represented using the VIolent Flows (ViF) descriptor. ViF descriptors are then classified as either violent or non-violent using linear SVM.

Why Violent Flows (ViF) descriptor ?

we are going to use the ViF descriptor because of the very low cost and acceptable accuracy. The ViF descriptor regards the statistics of magnitude changes of flow vectors over time as we see here:



In order to get these vectors, [1] used the optical flow algorithm proposed by [2] named Iterative Reweighted Least Squares (IRLS), but in this context, we used the ViF descriptor with Horn-Schunck [3] as optical flow algorithm proposed by [4].

The ViF descriptor is presented in algorithm [4], here we get a binary, magnitude-change, significance map bt for each frame ft. Then we get a mean magnitude-change map, for each pixel, over all the frames with the equation:

$$b_{x,y} = (1/T) \sum_{t} b_{x,y,t}$$

Then the ViF descriptor is a vector of frequencies of quantized values $b_{x,y}$.
Then the car crash detector is trained using a SVM classifier

Given a video sequence S of frames {f1, f2, . . .} we consider two related but different tasks. The first is anomaly classification: The video S is assumed to be segmented temporally, containing T frames portraying either anomaly or non-anomaly event

behavior. The goal is to classify S accordingly. The second is anomaly detection: Here, we assume an input stream of frames and the goal is to detect the change from anomaly to non-anomaly behaviour, with the shortest delay from the time (frame) that the change occurred. Moreover, as mentioned above, this goal must be achieved with processing performed faster than frame-rate.

Existing work [5] has shown that under certain circumstances, less than ten frames are required for reliable action classification. We consider such sub-second delays acceptable for a detection system and so reduce the second problem to the first by processing short frame sequences separately, classifying each one as either anomaly or non-anomaly, a detection is reported once an anomaly sub-sequence of frames is thus encountered.

ViF representation Algorithm

Given a sequence of frames “S”, we produce the VIolence Flows (ViF) descriptor by first estimating the optical flow between pairs of consecutive frames. This provides for each pixel $p_{x,y,t}$ where t is the frame index, a flow vector ($u_{x,y,t}$, $v_{x,y,t}$), matching it to a pixel in the next frame t + 1. Here, we consider only the magnitudes of these vectors:

$$m_{x,y,t} = \sqrt{(u_{x,y,t}^2 + v_{x,y,t}^2)}.$$

Doing so is in some sense a throwback to some early action recognition techniques which also relied on flow-vector magnitudes for processing actions [6]. There are some important differences, however, between those earlier approaches and our own.

Unlike previous methods, we do not consider the magnitudes themselves, but rather how they change over time.

Our rationale is that although flow vectors encode meaningful temporal information, their magnitudes are arbitrary quantities: they depend on frame resolution, different motions in different spatio-temporal locations, etc. By comparing magnitudes we obtain meaningful measures of the significance of observed motion magnitudes in each frame compared to its predecessor.

for each pixel in each frame we obtain a binary indicator $b_{x,y,t}$ reflecting the significance of the change of magnitude between frames:

$$b_{x,y,t} = \begin{cases} 1 & \text{if} \quad |m_{x,y,t} - m_{x,y,t-1}| \geq \theta \\ 0 & \text{otherwise} \end{cases}$$

Where θ is a threshold adaptively set in each frame to the average value of $|m_{x,y,t} - m_{x,y,t-1}|$. Doing so provides us with a binary, magnitude-change, significance map bt for each frame ft. We next compute a mean magnitude-change map by simply averaging these binary values, for each pixel, over all the frames ft ∈ S:

$$\bar{b}_{x,y} = \frac{1}{T} \sum_{t} b_{x,y,t}.$$

In its simplest form, the ViF descriptor is a vector of frequencies of quantized values $b_{x,y}$.
The ViF descriptor is therefore produced by partitioning b into M × N non-overlapping cells and collecting magnitude change frequencies in each cell separately. The distribution of magnitude changes in each such cell is represented by a fixed-size histogram. These histograms are then concatenated into a single descriptor vector.

Implementation

Here are the steps that we implemented in the program for Crashing Detection Module "Vif Descriptor":-

Input: List of Frames : Sequence of frames
Output : Histogram(bx;y; n_bins = 336)

1. Loop over frames.
2. Resize the frames to (134,100).
3. get prev, current and next frames using subsample of 3.
4. get optical flow for prev and current frame.
5. get optical flow for current and next frame.
6. calculate delta between the difference of their magnitudes.
7. get the mean of the delta and this is theta the limit.
8. if the pixal above the theta then increment 1 to the flow.
9. go to step 1 untill all frames processed.
10. get the mean of the flow.
11. Partition the frame to blocks and loop on them.
12. Calculate the histogram for every block Append to the feature vector.
13. Return the feature vector.

References

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