Detection of Salient Regions in Crowded Scenes

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The increasing number of cameras and a handful of human operators to monitor the video inputs from hundreds of cameras leave the system ill equipped to fulfill the task of detecting anomalies. Thus, there is a dire need to automatically detect regions that require immediate attention for a more effective and proactive surveillance. We propose a framework that utilizes the temporal variations in the flow field of a crowd scene to automatically detect salient regions, while eliminating the need to have prior knowledge of the scene or training. We deem the flow fields to be a dynamic system and adopt the stability theory of dynamical systems, to determine the motion dynamics within a given area. In the context of this work, salient regions refer to areas with high motion dynamics, where points in a particular region are unstable. Experimental results on public, crowd scenes have shown the effectiveness of the proposed method in detecting salient regions which correspond to unstable flow, occlusions, bottlenecks, entries and exits.

Introduction: Conventional CCTV monitoring by human operators becomes increasingly demanding as the average number of cameras deployed grows. Research findings have shown that besides fatigue and boredom, human attention tends to decline after 20 minutes. Therefore a high percentage of questionable activities, are often overlooked. This creates a moral dilemma when monitoring crowded scenes such as the footage of pilgrimages as shown in Fig. 1. Anomalous activity or behavior in a crowded scene can be very subtle and imperceptible to a human operator. Thus, an automated detection of suspicious regions is critical to direct the attention of security personnel to areas that require further investigation. Automated saliency detection is useful in numerous applications, such as identifying bottlenecks, which may help in avoiding congestion or evacuation planning.

Most work in saliency detection are focused on detection of salient regions in an image, where saliency originates from visual uniqueness and is often deciphered from image attributes such as colour, gradient and edges. Saliency in image differs from saliency in video sequence and regions in an image, where saliency originates from visual uniqueness like crowd instability and marathon). Fig. 1

![Sample shots of the different scenarios of crowded scenes (pilgrimage, train station and marathon).](image)

We adopt the Jacobian method as in [8], to measure the separation between particle’s paths which are seeded spatially close to a point, \( p \). Assuming that a particle’s position is slightly shifted from \( p \) at time \( t \) to \( p + \Delta p \) at time \( t + \tau \), the Jacobian, denoted as \( \nabla F_1(p) \), multiplied by the offset, \( \Delta p \), indicates the coordinate offset at time \( t + \tau \). This is based on the assumption that the displacement, \( \Delta p \), is small. The Jacobian of the flow map is computed by the partial derivatives of \( \Delta x \) and \( \Delta y \), where:

\[
\nabla F_1(p) = \begin{bmatrix} \frac{\partial \Delta x}{\partial \Delta y} \\ \frac{\partial \Delta y}{\partial \Delta y} \end{bmatrix}
\]

According to the theory of linear stability analysis, the square root of the largest eigenvalue, \( \lambda_1(p) \) of \( F_1(p) \) for \( F_1(p) \) indicates the maximum offset or displacement if the particle’s seeding location is shifted by one unit as it satisfies the condition that \( \ln(\lambda_1(p)) > 0 \). In the context of this study, a large eigenvalue indicates that the query point is unstable, and vice versa for a small eigenvalue. Since we are interested in regions that have high motion dynamics, based on the maximum eigenvalue, we can compute the stability of a point within its spatially close-neighbouring points using equation:

\[
\phi_t = 1 \left| \frac{1}{\tau} \log \sqrt[\tau]{\lambda_1(p)} \right|
\]

We propose two stages of segmentation that combine the output of first and coarse segmentation obtained from the local and global flow segmentation steps, followed by a flow magnification of regions with high motion instability to synthesize the signal, where \( \beta \) is the magnification factor and \( \alpha \) is the segmentation threshold:

\[
\phi_t = \begin{cases} \beta \phi_s, & \text{if } \phi_t \geq \alpha \\ (1 - \beta) \phi_s, & \text{otherwise} \end{cases}
\]
Experiment: Instability Detection: A set of 4 test sequences which comprise large scale crowd scenes were used for evaluation. The first sequence is obtained from the National Geographic documentary, 'Inside Mecca', while the second depicts a marathon scene. Synthetic noise was injected into both scenes to simulate instability in the motion of the crowd. A comparison between our work, Loy et al. and Ali et al. is performed. It is observed that all three methods are able to detect instability successfully as indicated by the red bounding boxes in Fig. 2. However, our method identified additional regions as salient. After a thorough investigation of the original sequence by 3 operators, we noticed that these regions correspond to areas where there are strong interactions motion dynamics within the crowd. It is worth noting that manual annotation of ground truth salient region due to bottlenecks or turbulence is an open issue because these types of salient regions are considered subjective. In the pilgrimage sequence, we noticed that the additional salient regions detected by our method in fact do correspond to regions where there are strong interactions motion dynamics. Due to the structure of the scene, or physical constraints of the Kaaba which is situated at the centre of the scene, the crowd tend to slow down their pace during the turning. In addition, the salient region detected near the synthetic instability is caused by the high motion dynamics near the entry and exit point. Thus, we argue that it is unfair to deem these detections as false positive. Instead, we presuppose if the detected regions can aid us in investigating and understanding the non-obvious motion dynamics of a scene.

(a) In addition to the ground truth unstable region (as enclosed in red and yellow bounding boxes), our method detected salient regions caused by bottlenecks (as highlighted in red blobs).

(b) Our method detects salient regions that may be caused by sudden slow down or potential danger due to high densities and instability.

Fig. 2. Sample comparison results (with synthetic noise).

Bottleneck Detection: We further validated the capability of our method by using the original sequences, where no synthetic instability is introduced as shown in Fig. 3. The detected bottleneck has tremendous potential as an indication of impending danger such as stampede taking place due to the stop-and-go waves in the crowd motion.

(a) Subtle saliency due to bottlenecks are detected by our method while state-of-the-art methods fail to detect these variations of saliency.

(b) Subtle saliency due to high densities and stop-and-go waves. State-of-the-art methods fail to detect such saliency.

Fig. 3. Sample comparison results (without synthetic noise).

Occlusion and Turbulence Detection: We further test the robustness of the proposed method by using other scenarios of large scale crowd; the school of fish and marathon sequence (where there is a lamp post obstructing the flow), the results are as shown in Fig. 4.

(a) The detected regions grow across the frames as the motion dynamics of the school increases. This sequence comprises a school of fish manoeuvring towards the center of the scene.

(b) The street light which simulates the scenario of occlusion or barrier, is detected (in red).

(b) The street light which simulates the scenario of occlusion or barrier, is detected (in red).

Fig. 4. Qualitative results on other scenarios of saliency by our method.

Conclusion: We have proposed a framework that detects salient regions by observing the flow activities in a given scene with minimal observations. In addition, the proposed method eliminates the need to track each object individually or prior learning of the scene, which is critical for real-time operation. Experimental results show that the proposed method is not only able to detect salient regions that correspond to clear instability, but bottleneck and occlusion which is often difficult to be noticed by the naked eyes. The promising results obtained are definitely worthy of future investigation since it is able to detect regions that would otherwise go unnoticed by the human operator. The capability of the proposed method in spotting patterns of crowd activities that are subtle play a very important role in triggering real-time alarm to alert of potential danger such as stampedes, failed evacuations and crushes for operational decision making.

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