STATISTICAL ANALYSIS OF PATHOLOGICAL MOTION AREAS

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Abstract

In this paper we address the problem of complex events in degraded image sequences. The occurrence of these complex events causes the failure of the motion estimation process. Consequently, the sequence of operations that rely on it, such as motion compensation and motion picture restoration, will fail as well. We present a statistical analysis of such areas, as well as a taxonomy of pathological motion. The results indicate that it is possible to discriminate between the complex events resulted from complicated object motion and the one resulted from image artefacts. An analysis scheme is proposed for the task of discriminating between the two cases.

Introduction

Recent developments in motion picture restoration show great improvements in noise reduction, flicker correction, blotch detection and removal etc. [Kok98, Roo99a]. However, there are situations where current techniques are still failing. In some of these cases, the quality of parts of the restored sequence is even degraded by the restoration process. For example, in sequences where objects or persons perform complex motion - called here “pathological motion”. The pathological motion represents motion that cannot be easily modeled by current motion estimation techniques. It can be observed in areas with fast or irregular motion, occlusions, scene entrances and/or other specific circumstances. When pathological motion occurs, the mistakes resulting from the motion estimation process will propagate into the motion compensation and image restoration processes. Here, restoration refers to the process of repairing the degraded areas of the image, rather than, for example, removing the motion blur (the latter can be even helpful by enhancing the impression of fast movement).

The pictures below show two restoration examples of regions with pathological motion. In the first one, a pigeon is flapping its wings vigorously, while in the second one the propeller of the left plane spins very fast. The failure of the motion compensation process determines the failure of the blotch detection and correction process. Thus, the restored versions show significant deteriorations of the semantic content. In the first sequence (Fig.1.a), several parts of the pigeon have disappeared, while in the second one (Fig. 1.b) the upper half of the first propeller is completely erased.

The usual procedure in case of pathological motion is to prevent the affected areas from being restored [Roo99b]. However, a more sophisticated method could be pursued, in order to try to restore these areas as well. To improve the detection scheme for pathological motion in degraded image sequences, a thorough analysis of this particular type of motion is essential. Based on this analysis, one can devise object tracking techniques [Rar00] that are able to deal with such complex motions. In this paper, we will approach only the first parts of the problem, mainly a study of general pathological motion and an analysis scheme for discriminating between pathological motion and artefacts.

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Basic Types of Pathological Motion

Estimating complex motion is still an open research subject [Wat94, Sez93, Mad98]. For deteriorated image sequences, the problem becomes even harder [Kok98, Roo99a, Roo99b], since motion estimation could then fail for two reasons: the pathological motion itself and/or the artefacts that affect the image sequence. Therefore, for restoration purposes, we propose that, in case of motion estimation failure, the underlying phenomenon to be called complex events (CE). CE can mean either pathological motion (PM) and/or artefacts, and we should discriminate them, in order to apply the proper restoration method.

Objects performing PM behave in many ways, either from the point of view of human perception, or from the point of view of the numerical contents of the affected areas. Based on these aspects, we have classified pathological motion as follows:

- **Blur**: This phenomenon is caused usually by a combination of factors: low sensitivity of the film/sensors array and improper shutter speed, compared to the relative movement between them and the objects, or improperly focused lens. As a consequence, objects look smeared, unclear. Motion blur, blur caused by strong zooming, or out-of-focus blur are different from the point of view of the point spread function associated with them.
- **Occlusion and uncovering**: The occlusion, either partial or total, may also cause the failure of a motion estimator. The uncovering represents the same case as the occlusion, if we take the frames in a reversed chronological order.
- **Large displacement** may render objects untrackable by common motion estimators usually because their displacement is larger than the search window.
- **Strong zooming** represents a problem for mainly the same reasons as a large displacement.
- **Intermittent motion** is an interesting aspect that we hardly observe when looking at image sequences displayed at normal speed. This kind of (semi-) repetitive motion is actually visible when we play the sequences frame by frame. The **blinking** subtype of intermittent motion is present when an object, or a part of it, is visible every other frame (e.g. the propellers of a plane). The **alternating** subtype shows up when an object displays its parts in a repetitive way across the frames (e.g. a pigeon flapping its wings, which are dark on one side, and bright on the other).
- **Image overlap** happens when the image of an object is a combination of at least two other images. This ranges from simple cases, like superposition of shadows or lights, to more difficult ones, in which an object is (semi-) transparent, or it reflects another image.
- **Erratic motion** is a very irregular motion that we can best describe by giving examples. A strongly waving flag is such an example. It cannot be classified as occlusion/uncovering because many parts of it appear only in one frame, in several consecutive frames. It cannot be classified as intermittent motion either because it is not repetitive. Another example is the image of a fire – the flames can split, merge, and change their shapes very fast. Wave crests or explosion-like phenomena also fall in this category.

While there are mathematical models for some of the above-listed types of motion, it is not the purpose of this paper to describe them into such detail. Although we tried to make the PM categories as independent as possible, it is certain that in some cases the detected PM will fall under two or more categories. This may happen because some of the aforementioned categories have, from certain points of view (e.g. color histogram), similar characteristics. Moreover, the detected PM may represent a combination of two or more categories (e.g. blur + large displacement).

Additional phenomena may contribute to the failure of a motion estimator: **interlacing and shot changes** (e.g. abrupt shot changes, dissolves, fadings, wipes). Hence, a detector of interlacing would be of help by switching from a frame-based to a field-based motion picture restoration. Also, a shot-change detector can help by detecting shot boundaries, thus preventing the motion estimator from taking into account frames from another shot.

Statistical Properties of the Pathological Motion Areas

Handling pathological motion would be virtually impossible if we would not know its characteristics. We have therefore performed a series of tests on areas with complex events, to see whether we can discriminate between artefacts and pathological motion. The tests consisted of histograms on different color schemes (RGB and YUV), extracted from areas with complex events. The tests did not comprise all categories of PM, but only a few of them, enough to give us a starting point.

In Fig. 2, we can see a rope moving very fast. As a result, the rope is completely smeared over the background. By taking the statistics of the blurred rope, on one hand, and those of the separate, clearly distinguishable rope and background in the next frame, on the other hand, we can see that the histograms of the blurred rope will fall between the histograms of the clear rope and background. This observation holds for all channels of an RGB image. It gives us an important piece of information when trying to classify CE areas. The same observation holds for YUV images, but the histograms of U and V channels are “squeezed” and more overlapped, since they represent mainly the difference between the Y channel, on one hand, and the B and R channels on the other. Thus, a YUV color space is not very useful in this type of analysis.
Fig. 2. Sequence “rope3”. a) Frame 50 - rope smeared over the background; b) Frame 51 – clear rope and background; c)-e) Histograms of the objects for the R, G and B channels.

In Fig. 3, we can see the same rope, this time only partially blurred by movement. The statistics of the blurred rope fall again between the statistics of the clear rope and background. This time, however, biased towards the foreground object (the rope). The underlying reason is that the foreground object is only partially blurred, and therefore it “melts” with the background only around its edges.

Fig. 3. Sequence “rope3”. a) Frame 48 - rope smeared over the background; b) Frame 47 – clear rope and background; c)-e) Histograms of the objects for the R, G and B channels.

A problem occurs where artefacts are present together with PM. For the time being we will consider only artefacts like scratches or blotches. Their appearance is known to be placed at the extremes of the color scale. Namely, they are usually either white or black (semi-transparent blotches are rare). Actually, as we will see in the next example, some of these artefacts can be detected even if they are not completely black or white.

Fig. 4 shows a rope that is blurred, and partially deteriorated by some blotches at the same time. The blotches are an interesting combination of bright and dark areas. Moreover, the bright areas are not white, but bluish-green. The histograms of the rope and impaired areas together show a main component in each of the RGB channels. These components lie between the components of the clear rope and background (not shown here), indicating a blurred motion. Apart from this, we can observe some “spikes” at the extremes of the histograms. Two such spikes appear on the right end of the G and B channels, corresponding to the bright blotches, while the right end of the R channel shows no significant values. These spikes explain the bluish-green appearance of some of the blotches. At the other extreme of the channels, the spikes indicate the presence of the dark blotches (in our case, the dark spikes are more evident in the R and B channels).
Fig. 4. Sequence “rope1”. a) Frame 57 - rope smeared over the background, with artefacts overlay; b)-d) Histograms of the rope for the R, G and B channels, with contribution of artefacts marked over. Artefacts show up only in some of the channels (see dotted ellipses).

We have also performed similar measurements over objects performing erratic motion. The resulted histograms have shown a high degree of similarity over the entire duration of the erratic motion.

Based on the results presented here, we can state that, given a complex events area, blotches and scratches can be separated from pathological motion by carefully studying the histograms for each of the R, G and B channels.

An Analysis Scheme for Complex Event Areas

In order to apply restoration techniques in CE areas, we must separate PM from artefacts. Based on this separation, we can further devise methods for the restoration of areas affected by artefacts. Classifying the pathological motion into the different subtypes is also useful, since the process of restoring the artefacts may need this information for deciding the proper restoration method. Fig. 5 displays the general processing flow for the complete restoration chain.

![Complex Event Detector](image1) ![Analysis Scheme](image2) ![Restoration](image3)

**Complex Event (CE) support map**  **Pathological motion (PM) and artefacts (A) support map**  **Restored area**

Fig. 5. General processing flow for the complex event areas.

In our case, the complex event detector is a method developed by Van Roosmalen [Roo99b]. This method makes use of a larger temporal aperture, in order to detect complex events that last for more than one frame (which is the usual behaviour of PM). Additionally, this method makes use of a sequence of steps including: mean filters, phase correlation, minimum absolute frame difference and other low-level operators. The output of the CE detector is used as input to our scheme.
Here, we propose an analysis scheme that classifies CE areas into PM and artefact segments, as shown in the second part from Fig. 5. The scheme consists of three sequential phases. Each phase tries to label parts of the CE areas. The remaining unlabeled parts are forwarded to the next phase. We have devised the three phases in order to speed up the classification procedure. Hence, the first phase will be the fastest one, while the third phase will be the slowest.

**Fig. 6. Scheme for separating pathological motion from artefacts. Phase 1 – detecting similarities between current complex event areas and previous CE segments.**

The first phase, shown in Fig. 6, will be triggered if we have already labeled segments of CE areas in the previous frame. We assume here that events from the past frame are likely to happen in the current frame as well. In other words, an object which performs some sort of pathological motion will do the same in the next frame. Similarly, an artefact (e.g. a scratch) from the past frame will also show up in the current one. Based on properties of the current CE areas (e.g. color, texture), we try first to find similarities between current CE areas and CE segments of the previous frame. If similarities are found, the regions will get the same label as the corresponding segments. It is important to observe that we compare entire CE areas of the current frame with just segments of the past CE areas.

**Fig. 7. Scheme for separating pathological motion from artefacts. Phase 2 – segmentation and inter-frame segment matching.**

The second phase, displayed in Fig. 7 will try to match parts of the current CE areas with parts from the past CE areas, or combinations of them. The idea here is that we may encounter some sort of PM (e.g. blur), that is a combination of other separate objects from the another frame. Thus, we segment the two frames and try to match segments from the CE areas of one frame with segments (or combinations of segments) from the CE areas of the other frame.

**Fig. 8. Scheme for separating pathological motion from artefacts. Phase 3 – inter-frame segment matching, including neighbouring segments.**

Finally, in the third phase, shown in Fig. 8, we assume that the pathological motion that might have caused our complex events is a combination of some past and current, semi-occluded, object. Since the object is semi-occluded, the neighbouring zones of the CE areas are presumably part of those objects and, consequently, they might have similar properties. To verify this, we will try to match segments of the current CE areas with combinations of segments from the
past CE areas plus neighbouring segments of the current CE areas. As a last step, if neither of the previous operations helped classifying the CE segments, the scheme will try to do that based on their (possible) extreme colors.

For the sake of simplicity, these schemes consider only two frames: the current one and the previous one. However, it is highly recommendable to take into account future frames as well. The proposed scheme is currently under development, and first results are expected to show up early this year.

Conclusions and Future Work

We have presented here a taxonomy of pathological motion, as well as findings about the statistical content of objects having a particular class of pathological motion. Moreover, we have presented statistics of pathological motion in the presence of artefacts. We have shown that, in principle, it is possible, based on these statistics, to discriminate between the two main forms of complex events, namely the pathological motion and the artefacts (at least, a few types of them). For this purpose, we have proposed a scheme for the classification of areas with complex events, where common motion estimators fail.

Future work will include the implementation of the proposed scheme, the collection of statistics for more types of pathological motion and artefacts, as well as the introduction of shot change detection techniques in the restoration process. For further improvements of motion picture restoration, we see object modeling and tracking methods [Rar00] as a qualitative step forward towards a higher level analysis of image sequences.

References


