Preliminary Visualization of Outdoor Video Content Using Principal Component Analysis*

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Abstract

In this paper, we visualized videos captured outdoors using principal component analysis (PCA) to facilitate the understanding of motion patterns relevant to safety and security monitoring. In the visualization, frames from videos depicting daytime airplane takeoffs and landings, nighttime airplane landings, small birds flying, and small birds resting on an elevated bridge were arranged on a two-dimensional plane according to their principal component scores. Our results show that the proposed visualization method positions frames in the two-dimensional space based on inter-frame correlations and is influenced by factors such as the size of moving subjects and changes in sunlight on the ground. This approach can contribute to safety and security applications, such as surveillance video analysis and anomaly detection, by allowing quick recognition of changes in subject movement and lighting conditions.

Keywords: Visualization, Video processing, Principal Component Analysis(PCA).

1 Introduction

In recent years, videos have increasingly been recorded in various public and private locations for safety and security purposes, such as monitoring facilities, transportation systems, and outdoor spaces. When an incident occurs, it is necessary to identify the problematic scene based on the information available at the time of the event. In such cases, the video must be reviewed to confirm its contents, which can result in a substantial amount of work, especially when the footage is lengthy. Therefore, it is necessary to reduce the workload of reviewing video content. With respect to finding specific scenes, many studies have focused on motion and action visualization (Botchen, 2008; Schoeffmann, Lux, Taschwer, & Boeszoermenyi, 2009; Schoeffmann K. T., 2009). Also, (Zhao, 2007) proposed a method for categorizing segmented scenes. Other researchers also have proposed various methods for

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categorizing video scenes. For example, (Liu, 2002) characterized video frames using a compact feature set created by repeatedly sorting and merging image features

In our previous works, to reduce the workload required to review numerous videos with long playback times, we have implemented average image compositing software (Sugita, 2022), video segmentation (Sugita, 2024), representative frame extraction from segmented videos (Sugita, 2025), and visualization of subjects and their motion in video using principal component analysis (Sugita, 2025). These approaches make the general motion of a person in indoor environments visually discernible, providing a basis for determining whether playback is necessary to review a particular video or scene. In this paper, we visualize specific aspects of outdoor videos using principal component analysis (PCA) and examine the influence of outdoor environments on the visualization results. By applying PCA to outdoor videos, we aim to provide a foundation for intuitive scene understanding and anomaly detection in safety and security contexts.

The paper is organized as follows. In Section 2, we introduce a method to visualize the video content using principal component analysis. In Section 3, we present some preliminary visualization results, and Section 4 concludes the paper.

2 Visualization of Video Content Using Principal Component Analysis

Reviewing video content through simple playback increases the review time proportionally to the video's duration (i.e., the number of frames). In this study, we focus on the differences between frames caused by camera movement and object motions, which are reflected as variations in subject appearance across frames.

As shown in Figure 1, we propose a method for visualizing subjects and their motion by arranging the frames that compose a video in a spatial layout based on their correlations. Principal Component Analysis (PCA) is a technique that represents a large number of correlated variables using a smaller number of composite variables, called principal components. In PCA, the variable space is compressed along new axes (principal components) so that as much of the original information as possible is retained. In conventional PCA, a covariance matrix is calculated from normalized data, and principal components are derived from the corresponding eigenvalues and eigenvectors. Since the covariance matrix of normalized data is equivalent to the correlation matrix, this study employs PCA to reduce the dimensions of the correlation matrix to two dimensions. This enables the visualization of subject motion by arranging video frames in a two-dimensional space based on their inter-frame similarity. Specifically, PCA is applied to the correlation matrix obtained from video frames to calculate the principal component scores for each frame.

In this method, a correlation matrix R ($n \times n$) is used to represent the relationships among video frames.

A composite variable Y is defined as a linear combination of the columns of R with coefficients a derived from the eigenvectors of R, as expressed below:

$$Y = a_1R_1 + a_2R_2 + ... + a_nR_n$$

Here, R_i is the i-th column of the correlation matrix R, and the coefficient vector a corresponds to the eigenvector of R.

The first principal component Y_1 represents the direction that maximizes the variance of the correlation matrix R. It is obtained using the elements of the eigenvector associated with the largest eigenvalue, as follows:

$$Y_1 = a_{11}R_1 + a_{21}R_2 + ... + a_{n1}R_n$$

Similarly, the second principal component Y_2 is defined as the composite variable whose coefficients correspond to the elements of the eigenvector associated with the second largest eigenvalue of R:

$$Y_2 = a_{12}R_1 + a_{22}R_2 + ... + a_{n2}R_n$$

Each frame is then plotted in a two-dimensional space, where the first principal component Y1 (PC1) is assigned to the x-axis and the second principal component Y2 (PC2) to the y-axis.

This visualization enables observation of relationships between frames: frames with similar content or motion are positioned closer together, while those with significant differences are placed farther apart. In this way, subject motions can be effectively visualized, providing an intuitive means to review video content.

3 Preliminary Visualization

In this visualization, 200 frames from the five outdoor videos depicted in Figure 2, which were captured at night and under 4 types of sunlight conditions with different subject sizes, were plotted on a plane according to their principal component scores. These videos are encoded in MP4 format, with HD quality (1280 x 720 pixels), and played at 30 frames per second (with a total of 1,800 frames, resulting in a playback duration of 1 minute). For each video, 200 frames were extracted at equal intervals, resized to 96 × 54 pixels, and plotted in a two-dimensional space. Scatter plots for each video are presented in Figures 3 - Figures 7, with PC1 on the x-axis and PC2 on the y-axis. The percentages shown with each axis label represent the proportion of variance explained by that component.

Figure 3 shows the scatter plot of all frames from a video of an airplane taking off from a runway. In the original footage, the airplane is visible during takeoff, and sunlit areas change according to cloud movement. Frames in the lower-left region of the scatter plot depict a landing airplane. In other regions, no landing airplane is visible, but cloud movement still causes changes in sunlight.

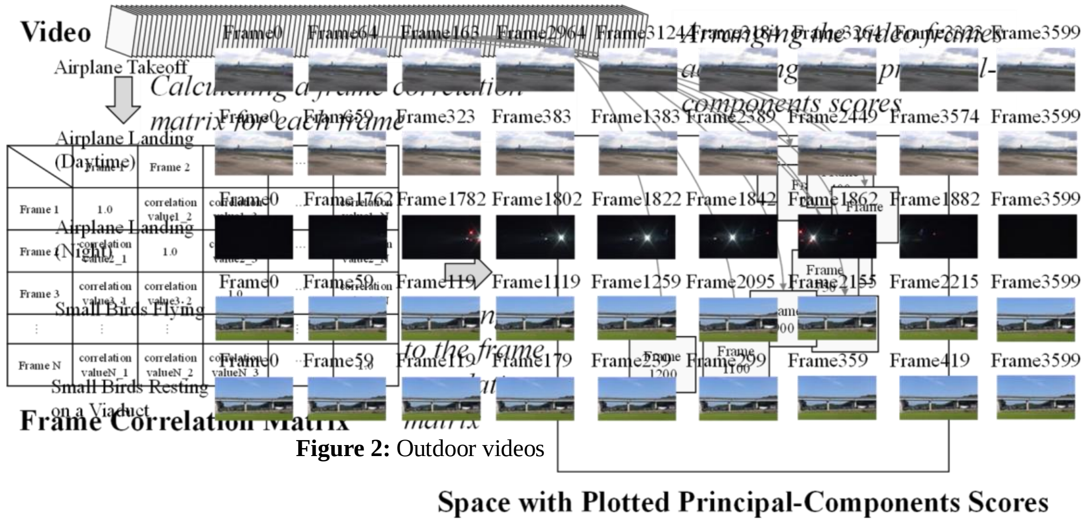

Figure 2: Outdoor videos

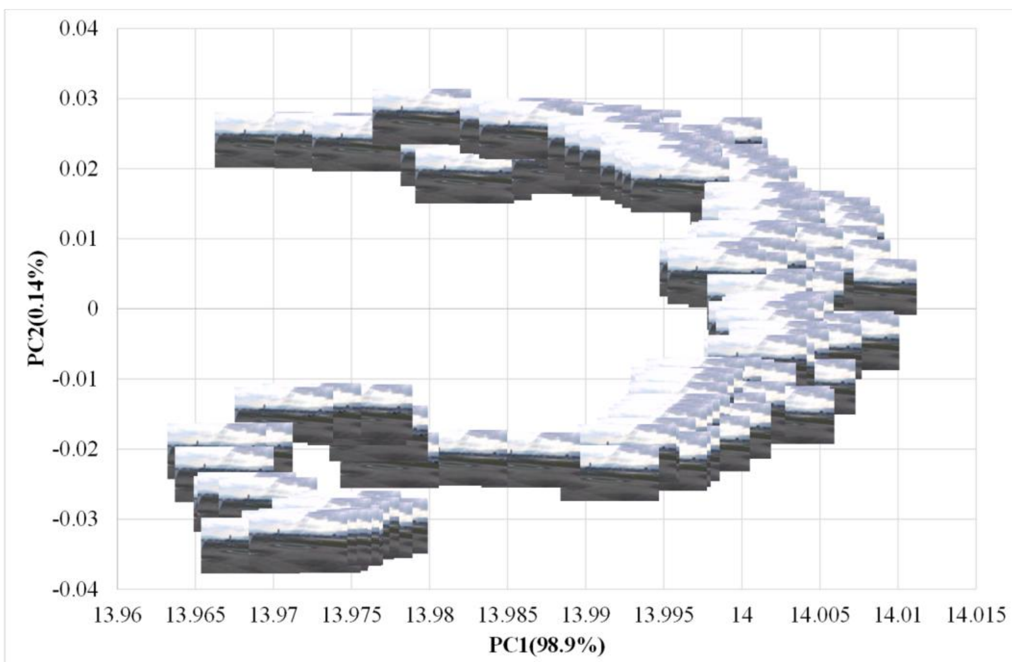

Figure 3: Visualization of Airplane takeoff during daytime

Figure 4 shows all frames from a video of an airplane landing on a runway. The airplane is visible during landing, with gradual changes in sunlit areas due to moving clouds and shifting rays of light. In the scatter plot, frames with the landing airplane are located in the left and bottom regions. The remaining frames capture only the changes in sunlight caused by clouds.

Figure 5 shows all frames from a nighttime landing video. The airplane crosses from right to left in the original footage. In the scatter plot, frames showing the landing process are arranged toward the outer regions, while those without the airplane appear slightly right of center.

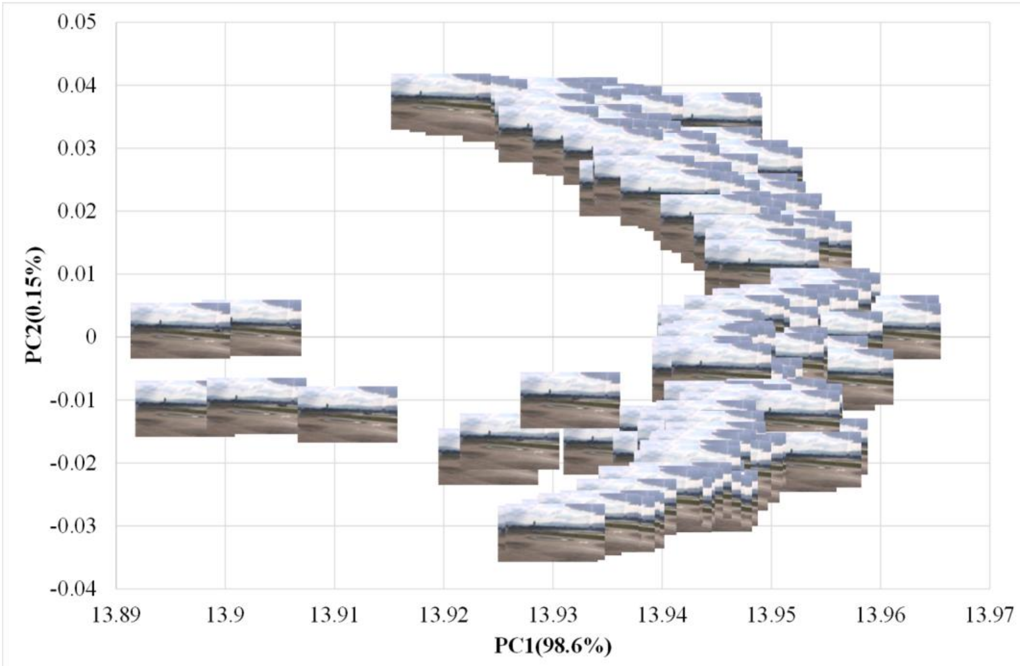

Figure 4: Visualization of Airplane landing during daytime

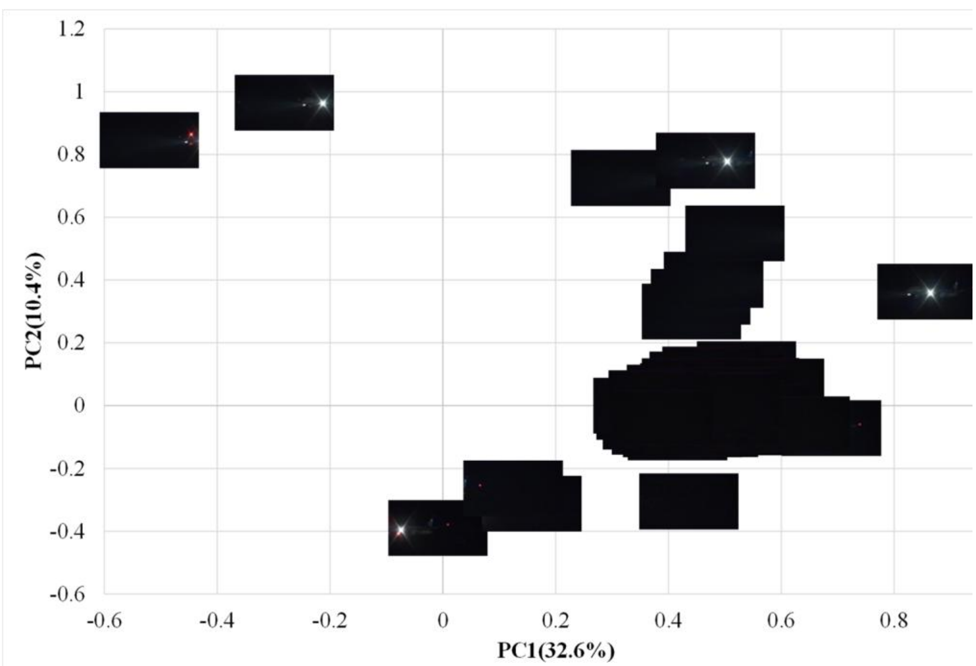

Figure 5: Visualization of Airplane landing during night

Figure 6 shows all frames from a video of small birds in flight, accompanied by vehicles moving on an elevated bridge. In the scatter plot, frames showing vehicles on the bridge appear in the lower-left region. However, scenes of flying birds are dispersed among other frames, making their positions in the plot unclear.

Figure 7 shows all frames from a video of small birds resting on an elevated bridge after flight. In the scatter plot, frames depicting both resting and flying birds are intermixed with other frames, again making their locations in the plot unclear.

4 Conclusions

In this paper, we visualized videos captured outdoors using PCA. In the visualization, frames from videos of daytime airplane takeoffs and landings, nighttime airplane landings, small birds flying, and small birds resting on an elevated bridge were arranged on a two-dimensional plane according to their principal component scores. The results show that in the daytime airplane videos, the principal component scores were strongly influenced by sunlight conditions affected by cloud movement, which in turn determined the positioning of frames. Because the airplanes appeared relatively small in the videos, their movements had little effect on frame placement. Furthermore, in the nighttime airplane landing video, frames without the airplane clustered densely near the center, while frames showing the airplane were positioned toward the outer edges of the two-dimensional plane. On the other hand, in the videos of small birds flying and resting, because the subject birds were small, their movements had little impact on the frame placement. Instead, the influence of larger moving vehicles was more significant. These results indicate that our visualization method, which positions frames in two-dimensional space based on inter-frame correlations, is influenced by factors like the size of moving subjects and changes in sunlight on the ground.

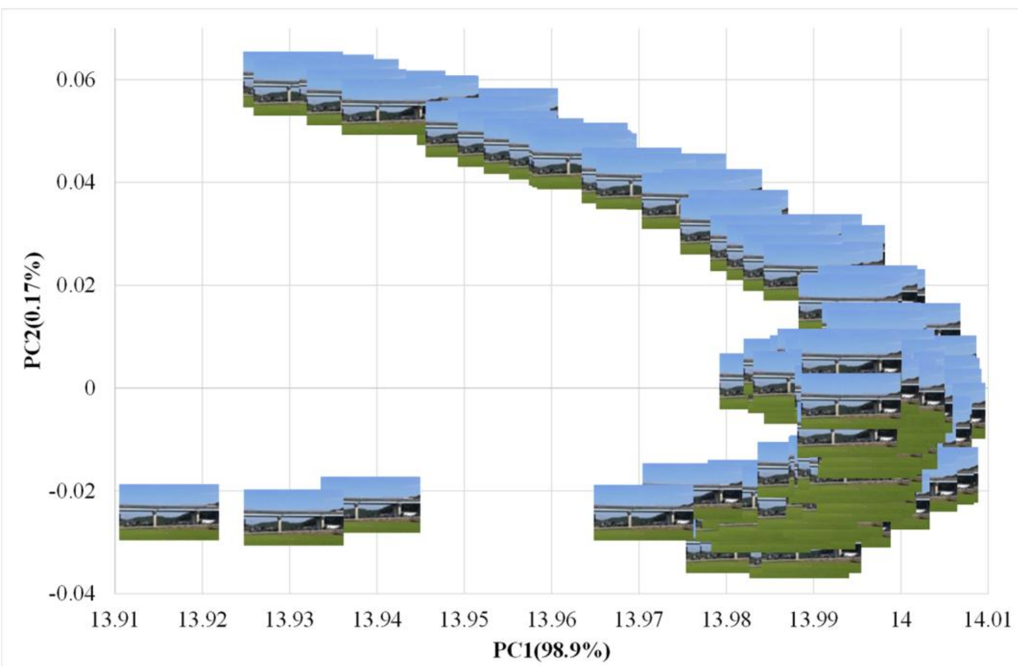

Figure 6: Visualization of small birds flying

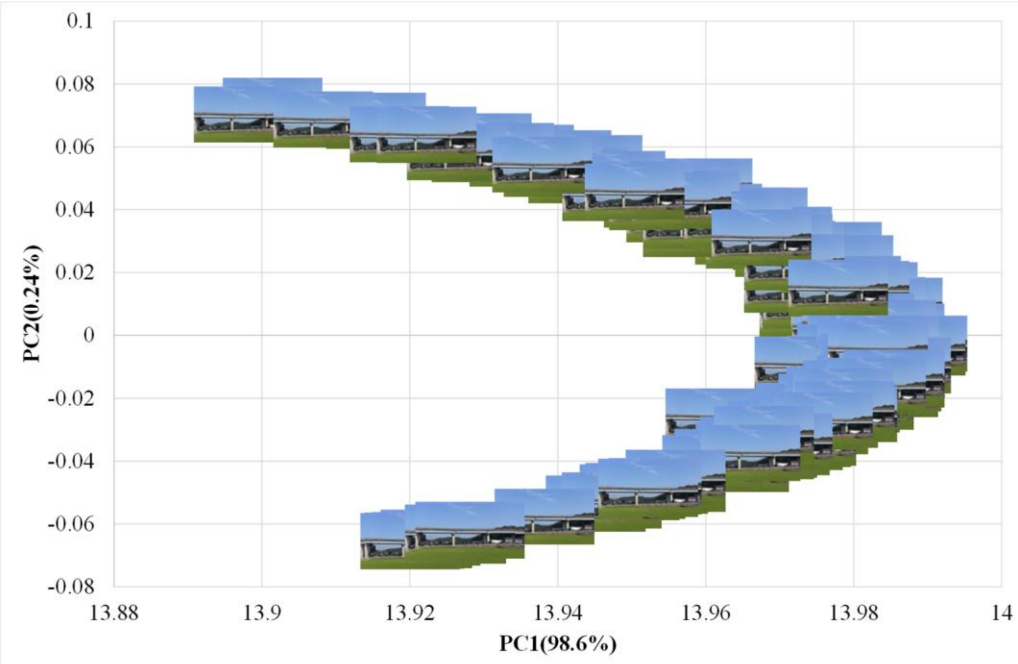

Figure 7: Visualization of small birds resting on an elevated bridge

These characteristics suggest that the proposed visualization method could be useful for efficiently reviewing and interpreting outdoor surveillance videos. By enabling an overview of long-duration videos through two-dimensional visualization, the method has the potential to assist in identifying scene changes or unusual motion without the need for exhaustive playback.

In the future, we would like to analyze the effects of the size of monitored subjects and changes daylight in video on the proposed method. Also, we will improve the processing time and visualize various types of videos. Furthermore, we will increase the number of participants in the questionnaire survey in order to improve the paper quality.

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