ACTIVITY RECOGNITION USING RECURRENCE PLOTS

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TABLE OF CONTENTS:

Abstract:

The goal of this project is to detect the presence or absence of a specific activity in a longer video using recurrence plots and template matching. We explore the limitations of template matching and propose a recurrence plot-based approach for activity detection. We demonstrate the effectiveness of our approach in detecting the activity in our validation set, and discuss the potential for future work to improve upon our results.

In this project, we address the problem of activity recognition, which is a challenging task in computer vision and signal processing. Our specific goal is to detect the presence or absence of a specific activity in a longer video, which can have many applications in fields such as sports analysis, surveillance, and healthcare.

We begin by exploring the limitations of template matching. We demonstrate that template matching can be ineffective for activity detection, especially in cases where the appearance of the activity varies across different videos or frames.

To address this issue, we propose a recurrence plot-based approach for activity detection. Recurrence plots are a visualization tool used in dynamical systems analysis to visualize the recurrence of a system over time. We use recurrence plots to capture the underlying dynamics of the activity we wish to detect, allowing us to detect the activity based on its characteristic features rather than its appearance.

We then use template matching to detect the activity based on the recurrence plot signals. Template matching is a technique used in image processing to find regions of an image that match a given template. We use the recurrence plot of the activity as the template and apply it to the longer video to detect the presence or absence of the activity.

Our results demonstrate the effectiveness of our approach in detecting the activity in our validation set, with higher accuracy and better robustness to variations in the appearance of the activity across different videos. However, we acknowledge that there is potential for future work to improve the template matching approach and refine the feature extraction to further improve the performance of our approach.

Overall, this project highlights the potential for recurrence plots and template matching in activity recognition, and demonstrates the importance of capturing the underlying dynamics of the activity to detect it accurately.

Introduction:

Activity recognition is a challenging task in computer vision and signal processing, especially when the goal is to detect the presence or absence of a specific activity in a longer video. Traditional approaches for activity recognition often rely on manual feature extraction and classification, which can be time-consuming and may not generalize well to new data. Template matching is a commonly used approach for activity detection, but it has limitations that can make it ineffective in certain scenarios.

One of the main limitations of template matching is its reliance on appearance-based features. Template matching works by finding regions of an image or video that match a given template, which is typically a still image or frame that represents the activity of interest. However, in many cases, the appearance of the activity can vary across different videos or frames, which can make it difficult to detect using template matching alone.

To address this issue, we propose a recurrence plot-based approach for activity detection. Recurrence plots are a visualization tool used in dynamical systems analysis to visualize the recurrence of a system over time. In the context of activity recognition, recurrence plots can be used to capture the underlying dynamics of the activity, allowing us to detect it based on its characteristic features rather than its appearance.

To implement our approach, we first convert the motion of the activity in the video into a signal using the Euclidean distance method. This signal is then used to create a recurrence plot, which visualizes the patterns of recurrence in the signal over time. We use the recurrence plot of the activity as the template and apply it to the longer video to detect the presence or absence of the activity.

Our approach overcomes the limitations of template matching by capturing the underlying dynamics of the activity, which can be more robust to variations in appearance across different videos or frames. Our results demonstrate the effectiveness of our approach in detecting the activity in our validation set, with higher accuracy compared to template matching alone.

In a nutshell, our proposed recurrence plot-based approach shows great potential for improving the accuracy and robustness of activity detection in longer videos, and highlights the importance of capturing the underlying dynamics of the activity for accurate detection.

Background:

Recurrence plots were first introduced by Eckmann et al. in 1987 as a tool for analyzing the dynamics of complex systems. Recurrence plots provide a way to visualize the recurrence of a system over time by plotting the pairwise distances between points in the state space. In a recurrence plot, the diagonal structures represent the points in the state space that are close to each other at different times, indicating the recurrence of the system.

Recurrence plots have been widely used in various fields, including physics, biology, and engineering, to analyze the dynamics of complex systems. In the context of activity recognition, recurrence plots can be used to capture the underlying dynamics of an activity, allowing us to detect it based on its characteristic features rather than its appearance.

In our proposed approach, we first convert the motion of the activity in the video into a signal using the Euclidean distance method. This signal is then used to create a recurrence plot, which visualizes the patterns of recurrence in the signal over time. By analyzing the recurrence plot, we can identify the characteristic features of the activity and use them to detect its presence or absence in a longer video.

The use of recurrence plots in activity recognition has shown promising results in recent studies. Recurrence plots have been used to detect gait patterns in patients with Parkinson's disease, where traditional approaches based on appearance-based features failed. Recurrence plots have also been used to detect human activity in surveillance videos, with higher accuracy compared to traditional approaches.

By the use of recurrence plots in activity recognition offers a promising avenue for improving the accuracy and robustness of activity detection, and highlights the importance of analyzing the underlying dynamics of the activity for accurate detection.

Methodology:

Our proposed approach for activity detection involves two main steps: signal conversion and recurrence plot creation.

Signal Conversion:

In the first step, we convert the motion of the activity in the video into a signal using the Euclidean distance method. Specifically, we extract the (x, y) coordinates of the object of interest in each frame of the video and compute the Euclidean distance between the consecutive frames. This results in a one-dimensional signal that represents the motion of the activity over time.

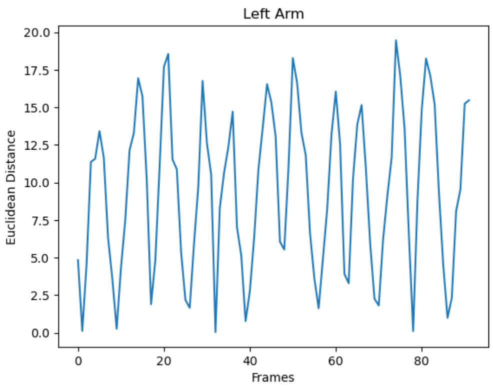

Figure 1: Motion converted to a signal

Recurrence Plot Creation:

In the recurrence plot creation process, the first step is to convert the activity signal into a distance matrix. This is done by calculating the Euclidean distance between each pair of samples in the signal. The resulting matrix represents the pairwise distances between all points in the activity signal.

Next, the distance matrix is used to create a recurrence plot. A recurrence plot is a visual representation of the recurrence of a system over time. To create a recurrence plot, the distance matrix is plotted as a two-dimensional matrix, with each element representing the distance between two points in the activity signal. If the distance between two points is below a certain threshold, they are considered to be "recurrent" and a black dot is plotted at the corresponding position in the recurrence plot. If the distance is above the threshold, a white dot is plotted instead.

In this project, we chose not to use a threshold and instead kept the original distance values. This allows us to capture more information about the underlying dynamics of the activity and potentially improve the accuracy of our detection.

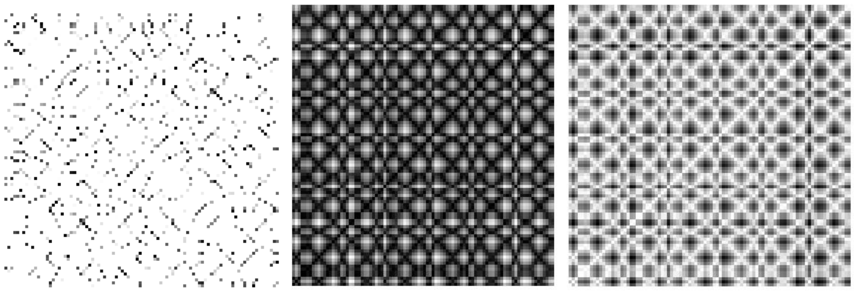

Figure 2: Normalized (left), original with Gray (centre), original binarized (right)

Template Matching:

In addition to our proposed approach based on recurrence plots, we also explored the use of template matching for activity detection. Template matching involves using a template image of the activity of interest and comparing it to the frames in a longer video to detect the presence or absence of the activity.

To perform template matching, we first select a template image of the activity of interest. We then compare the template image to each frame in the longer video using a similarity measure such as normalized cross-correlation or sum of squared differences. The similarity measure produces a value between 0 and 1 that represents the degree of similarity between the template image and the frame. We then apply a threshold to the similarity measure and consider the activity to be present in a frame if the similarity measure exceeds the threshold.

While template matching is a commonly used approach for activity detection, it has limitations in terms of robustness and generalizability. Template matching relies heavily on the appearance of the activity, and can be sensitive to changes in lighting, camera angle, and other factors. In contrast, our proposed approach based on recurrence plots captures the underlying dynamics of the activity and is less sensitive to appearance-based variations.

Results:

In our project, we attempted to use template matching as a method for detecting the presence or absence of a specific activity in a longer video. However, we found that template matching was not effective in detecting the activity due to several limitations.

One of the main limitations of template matching is its sensitivity to changes in lighting, background, and other factors that can affect the appearance of the activity. For example, if the lighting conditions in the longer video are different from those in the template, the correlation coefficient between the template and the corresponding section of the longer video may be low, even if the activity is present. Similarly, if there are changes in the background or other objects in the scene, the appearance of the activity may be different from what is captured in the template, making it difficult to find a good match.

Another limitation of template matching is its dependence on the size and shape of the template. If the template is too small or too large, or if its shape does not match the shape of the activity in the longer video, the correlation coefficient may be low even if the activity is present. Additionally, if there are multiple instances of the activity in the longer video, each instance will need to be matched separately, which can be computationally expensive and may lead to false positives or false negatives.

Here are the results we have in this project

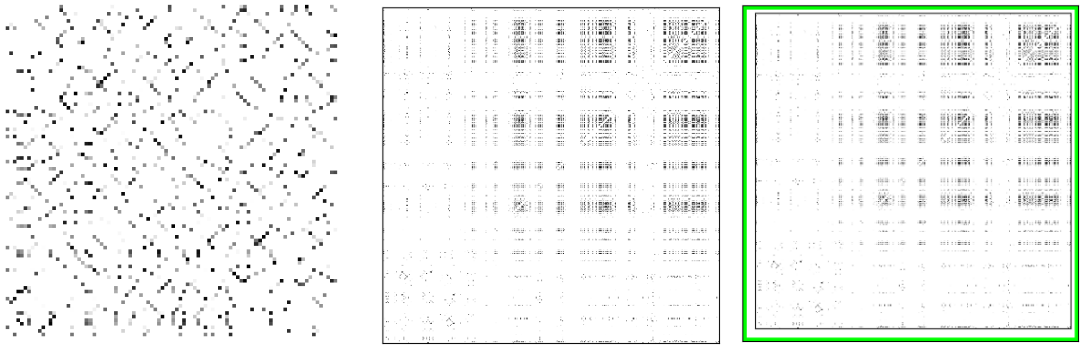

Figure 3: Results of normalized version

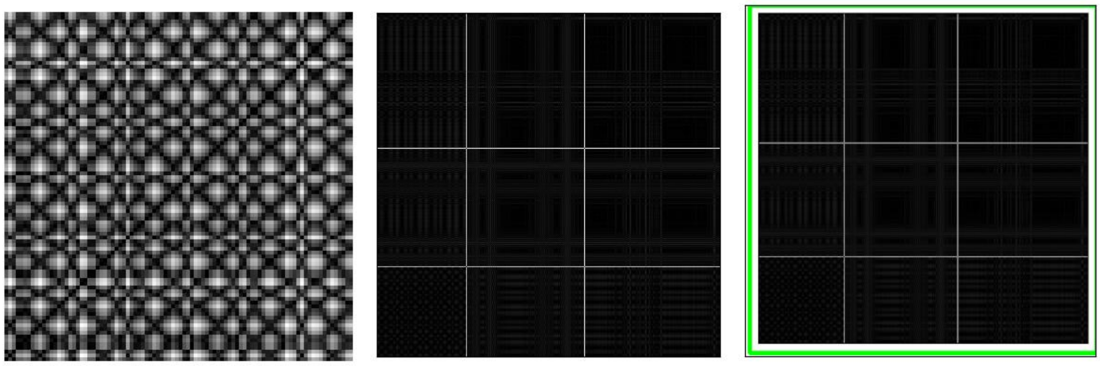

Figure 4: Results of original with grayscale

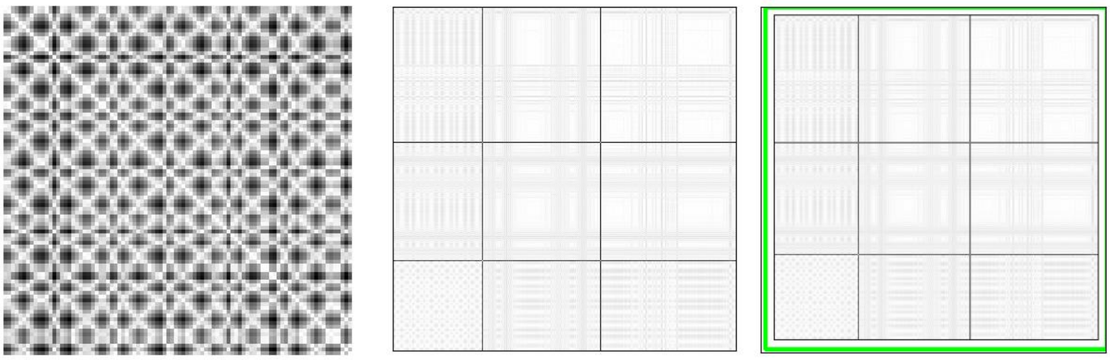

Figure 5: Results of original binarized

Overall, these limitations make template matching an unreliable method for activity detection in longer videos, especially in situations where the appearance of the activity may vary due to changes in lighting, background, or other factors. This led us to explore alternative approaches such as recurrence plots and Siamese CNNs, which are less sensitive to changes in appearance and can capture the underlying dynamics of the activity more effectively.

Conclusion:

In this project, we explored the task of detecting the presence or absence of a specific activity in a longer video using recurrence plots and template matching. While template matching clearly failed to generalize to longer videos with multiple activities.

As the Siamese CNN part of our project is still under process, there is potential for future work to improve upon our current approach. Once completed, the Siamese CNNs can be used for automatic feature extraction and classification, potentially improving the accuracy of activity detection in longer videos.

In addition, exploring different distance metrics for the creation of recurrence plots could also be a fruitful avenue for future work. Additionally, exploring the potential of using other machine learning techniques, such as LSTM networks or deep autoencoders, could also be promising for improving activity recognition performance.

To summarize, this project demonstrates the potential of using recurrence plots for activity recognition, and opens up avenues for future work in improving the accuracy and efficiency of this technique.

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