PROBABILISTIC HOME VIDEO STRUCTURING: FEATURE SELECTION AND PERFORMANCE EVALUATION

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Abstract: We recently proposed a method to find cluster structure in home videos based on size.

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FEATURE SELECTION AND PERFORMANCE EVALUATION: PROBABILISTIC HOME VIDEO STRUCTURING
Introduction

1. Our Approach

The paper is organized as follows. Section 2 describes the video information extraction and detection. Section 3 presents the formulation of our detection procedure. Section 4 describes the video information detection and the effect of video information. With respect to content detection, we propose a novel detection model on video information. In the third block, we present a detailed evaluation of the performance of our model on video information. In the second section, we analyze the characteristics of some detection results using different parameters in order to obtain the most suitable parameter combination of different parameters. The experiments show that our method can be used to improve the detection performance of video information. In the next section, we analyze the performance of our model on video information. The experiments show the performance of our model on video information. In the last section, we analyze the performance of our model on video information. The experiments show the performance of our model on video information.
3.2 Selection of Visual Features

condensation function of $\phi$.  The $L^2$ norm of the $\phi$-operator based on the B-spline is defined as $\phi(x) = \int_{-\infty}^{\infty} |x|^2 \, dx$.  In this case, the similarity between B-spline functions is expressed by the inner product $\langle \phi_i, \phi_j \rangle = \int_{-\infty}^{\infty} \phi_i(x) \phi_j(x) \, dx$.  The similarity between two B-splines $\phi_i$ and $\phi_j$ can then be computed by taking the inner product $\langle \phi_i, \phi_j \rangle$.

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**Figure 1**: Intensity hierarchy

![Figure 1](image1.png)

3.3 Extraction of Visual Features

In our video analysis, we computed the features of the RGB and HSV spaces, color reduction, edge detection, and intensity hierarchy.  In this case, the similarity between B-spline functions is expressed by the inner product $\langle \phi_i, \phi_j \rangle = \int_{-\infty}^{\infty} \phi_i(x) \phi_j(x) \, dx$.  The similarity between two B-splines $\phi_i$ and $\phi_j$ can then be computed by taking the inner product $\langle \phi_i, \phi_j \rangle$.

Home video clips usually contain more than one appearance, due to the fixed hand-held camera.

3 Feature Extraction and Selection

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3.3 Selection of Temporal Features

In this section, we will discuss various methods for selecting and using temporal features in our analysis. These features are crucial for understanding the dynamics of the system under study. We will focus on two main categories: (1) features that capture the temporal evolution of a single event, and (2) features that relate multiple events temporally.

The first category of features includes measures such as duration, frequency, and intensity. These features are particularly useful for capturing the time span over which an event occurs. For example, the duration of an event is a common feature used to describe how long an event lasted.

The second category of features involves analyzing the relationships between events. This includes features that capture the temporal proximity of events, such as the time interval between two events. These features are useful for understanding how events are clustered in time.

To illustrate these concepts, we have included several diagrams that depict different temporal features. Each diagram represents a different aspect of temporal behavior, and they are designed to help visualize the relationships between events.

### Summary

- **Duration**: This feature captures the time span of an event. It is defined as the difference between the start and end times of an event.
- **Frequency**: This feature measures how often an event occurs within a given time frame.
- **Intensity**: This feature represents the magnitude of an event over its duration.
- **Temporal Proximity**: This feature captures the time interval between two events, which can help identify patterns in event occurrence.

By combining these features, we can gain a more comprehensive understanding of the temporal dynamics of the system under study.
the text is not legible due to the quality of the image. It appears to be a page from a document discussing scientific or technical content, possibly related to performance evaluation or some form of data analysis. The text is dense and appears to be formatted in a table or list format, which is not legible in the current image. Due to the low quality of the image, it is not possible to provide a meaningful transcription.
of knowledge of the problem. Measuring should be discouraged as more video classes consist of

The choice of the prior distribution is shown in Table 2. A uniform prior does not make use

For the posterior of the probability of correct class operation (PC), a uniform prior is used for the corresponding

for every element $i$ of the vector is $\text{Pr}(x_i = 1 - \text{Pr}(x_i = -1))$. The posterior of the probability of correct class operation $P(x_i | \text{Pr}(x))$ is a normal distribution. Assuming a uniform prior, the expression for the posterior distribution becomes

Using the Bayesian approach, we observe steps in error of $N$ of the likelihood.

<table>
<thead>
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<th>Method</th>
<th>Positive Class</th>
<th>Negative Class</th>
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<tr>
<td></td>
<td>0.2</td>
<td>0.8</td>
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<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 2: Shot Decisiveness Performance

Cardinal Danes consistent with the performance in terms of decision assistance, for which both value and

stability, so any random distribution would be equally good.

demonstrate approaching (c) the posterior of the probability of correct class operation.
a number of clues for probabilistic video structuring. The obtained results are encouraging.

5 Concluding Remarks

Figure 3: (a-d) Frames extracted from parts of video shows that were exceptionally matched by our

methodology.

from shows correspond to the video sequence, the middle nodes in the clusters, and the labels to random frames.

Figure 4: Examples of video structuring on two family video sequences (details). The root node

Table 1: Effect of Prior Probability

<table>
<thead>
<tr>
<th>Prior Probability</th>
<th>Successful</th>
<th>Failed</th>
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<tbody>
<tr>
<td>0.28</td>
<td>0.72</td>
<td>0.13</td>
</tr>
</tbody>
</table>
References

Home Video Databases.

Acknowledgements

Several of the analyzed video sequences belong to the European kitchen.


