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Music-Guided Video Summarization using Quadratic Assignments

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ABSTRACT
This paper aims to automatically generate a summary of an unedited video, guided by an externally provided music-track. The tempo, energy and beats in the music determine the choices and cuts in the video summarization. To solve this challenging task, we model video summarization as a quadratic assignment problem. We assign frames to the summary, using rewards based on frame interestingness, plot coherency, audio-visual match, and cut properties. Experimentally we validate our approach on the SumMe dataset. The results show that our music guided summaries are more appealing, and even outperform the current state-of-the-art summarization methods when evaluated on the F1 measure of precision and recall.

CCS CONCEPTS
- Information systems → Multimedia content creation;  
- Mathematics of computing → Permutations and combinations;

KEYWORDS
Video Summarisation, Quadratic Assignment Problem

1 INTRO
The goal of this paper is to create high-quality video summaries, guided by an externally provided music-track. Consider for example that after a day of skiing with your GoPro camera, you reflect your mood by selecting a music-track and the computer will automatically create a video summary of your skiing day fitted on this specific music-track. Clearly a summary with classical music should have different dynamics, plots, and cuts than a summary based on funk music, even when the summaries are created from the same source video. Such an adaptive summarization method could be useful for creating video summarizations of social events by social media services or to personalize video summarizations.

1.1 Related work
Video summarization is often simplified to a frame interestingness problem [18], where interestingness can be measured using a variety of approaches, including object detections [11, 13], saliency [5, 8, 14], person detection [17], and landmark detection [12]. However, frame interestingness does not include any clues about the aesthetics of the summarization itself. Rather than relying exclusively on heterogeneous measures of interestingness for our video summarization, we emphasize on creating summaries, with a coherent plot and logical cuts.

Several works have previously incorporated coherency to make video summaries more viewer friendly. Such coherency can be performed by selecting sets of consecutive frames [5] or by adding temporal regularization [11]. The balance between interestingness and coherency, can be obtained using pre-segmentation methods [5], submodular optimization [6, 19] or recurrent neural networks [22].
We see video summarization as classical assignment problem, where the assignment depends on three major factors:

- the interestingness of the frame;
- the match between the music in the summary and the visuals of the specific frame;
- the match with the previous frame in the summary, to model a story-line, segments, and cuts.

While frame-relevance yields a selection problem, and the music-video match can be modeled as a linear assignment problem, to model the cost for the subsequent frames we need to resort to quadratic assignment problems (QAP). Originally introduced for allocating facilities to certain locations in 1957 by Koopmans and Beckman [9], the QAP suits our model for music-guided video summarization. It enables to start from the summary, without the need of any pre-segmentation which would limit the flexibility to adjust to a specific music-track.

The QAP is a permutation problem, which aims to find the permutation $P \in \mathcal{P}$ with the highest reward:

$$f_{\text{QAP}}(\bar{P}) = \text{tr} \left( (FPR^T + B) \bar{P}^T \right),$$

where $F$ denotes the flow matrix defined over the slots in the summary, and $R$ defines a reward matrix between the frames in the source video, the last term $B$ is a linear summary-source reward matrix, see Fig. 2 for an overview. Note that our permutation $P \in \mathcal{P}$ also encompasses a selection, since the summary contains less frames than the original source video. Therefore for any valid permutation $P$ holds: $\sum_{j=1}^N p_{ij} = 1$ and $\sum_{i=1}^S p_{ij} = 1$.

Below, we introduce 6 summary components to model the three major factors of a good summarization, mentioned above. These components include, frame interestingness (I), Uniformity of storyline (U), Audio-Video Dynamics (AVD), Segment Length (SL), Motion Boundaries (MB), and Beat Cuts (BC). Each of these component is modeled as an assignment problem, and our final model is a weighted combination of these $c$ components:

$$f_{\text{AVsum}}(\bar{P}) = \sum_c w_c f_{\text{QAP}}^c(\bar{P}).$$

In general, solving a QAP, or its $\varepsilon$-approximate solution, is a NP-hard problem [16], in Section 2.4 we discuss our search strategy.

### 2.1 Frame interestingness

The first factor is the interestingness of each frame, for which we learn a frame-based interestingness classifier, using the human selected summaries as positive examples and the remaining frames as negative examples. For each frame we extract a set of $M$ features,
and compute the interestingness score for frame $k$ based on unary and pairwise terms, following [5, 11] we use:

$$i^k = w_0 + \sum_{m=1}^{M} w_m x_{m}^k + \sum_{m=1}^{M} \sum_{n=m+1}^{M} w_{mn} x_{m}^k x_{n}^k,$$

(3)

where $x_{m}^k$ denotes the score of the $m$-th feature of the $k$-th frame.

Maximizing the interestingness of a summary is in principle (just) a selection problem, to remain within the QAP formulation, we define the linear matrix $B^I$ to have identical values for each location $s$, given a frame $k$, as follows:

$$B^I_{sk} = i^k.$$

(4)

Uniform Storyline. Besides the frame interestingness factor, we also observe that the source videos tell a roughly temporal uniform coherent story. This was also observed in [6], and indicates that a priori a good summary samples frames uniformly from the source video. Such a uniform sampling reward can be modeled as the linear part of the QAP, measuring the distance between summary position $s$ and its uniform sampled frame $\tilde{p}_s$ from the source video:

$$\tilde{p}_s = \frac{s}{N} (s - \frac{1}{2})$$

(5)

$$B^U_{s,n} = 1 - \frac{1}{2} \left( \tilde{p}_s - n \right)^2,$$

(6)

where $B^U$ is normalized between 1 (when $n = \tilde{p}_s$) and 0, illustrated in Fig. 3. This could be seen as a prior model to retain uniform temporal coherency of the source video.

2.2 Music-Video Match

The second factor is the match between the music-track in the summary and the visuals of the source video. In this paper we aim to let the summary follow the audio dynamics, and therefore that the music dynamics should be similar to visual dynamics. To determine the audio dynamics we compute the relative amplitude for each summary frame location: $\tilde{a}^s = a^s - \frac{1}{N} \sum_{s'} a^{s'}$, where $a^s$ is the amplitude at time $s$. For the video dynamics we compute the relative motion per frame: $\tilde{f}^n = f^n - \frac{1}{N} \sum_{k} f^k$, where $f^n$ indicates the motion in frame $n$, based on the computation of the optical flow. We use the following linear rewards:

$$B^{AVD}(s,m) = 1 - \gamma |\tilde{a}^s - \tilde{f}^m|,$$

(7)

where $\gamma$ is a constant normalizing all rewards between 0 and 1.

2.3 Subsequent Frames

The last factor is to model the relation between two subsequent frames in the summary. This is important given that our model does not use pre-segmentations of the video. Subsequent frames could either form a consecutive segment, or define a cut (jump). The final model should balance between the length of series of consecutive frames, the placing of the cuts based on the frame features and based on the alignment with the music-track, and to represent the storyline of the original video.

Segment length. First, we model the length of a segment, since too short segments results in many cuts and makes the summary chaotic, while too long segments make the summary boring. Therefore we include a score based on the segment length $l$:

$$s(l) = \max(0, l_p - |l - l_p| - l_m)$$

(8)

where $l$ is the length of a segment, $l_p$ the prior length, and $l_m$ the minimum length, see Fig. 4 (top). In QAP formulation, this entails the following flow and reward matrices:

$$R^{SL}(m,n) = \begin{cases} 2 & \text{if } n=m+l_p, \\ 1 & \text{if } m=n+2l_p-l_m, \\ 0 & \text{otherwise} \end{cases}$$

(9)

$$F^{SL}(s,t) = \delta(s=t+l_m) - \delta(s=t+l_p) + \delta(s=t+2l_p-l_m) - \delta(s=t-l_m),$$

(10)

where the flow matrix $F$ uses the Dirac delta function $\delta(\cdot)$, which returns 1 if and only if the condition is true. The complexity of these matrices originate to ensure that coincidental rewards are canceled, e.g. a jump of exactly $l_p$ frames would normally add an additional reward for a good sequence, yet due to the jump this needs to be zeroed.

Motion boundaries. Besides the segment length, we also have an aesthetic view on cuts, namely, a cut should take place when there is a minimum of motion in the frames, see Fig. 5. This is included in the QAP, by using the following flow and reward matrices:

$$R^{MB}(m,n) = \frac{1}{2} \delta(m > n+1) (x_m^n + x_m^m),$$

(11)

$$F^{MB}(s,t) = \delta(s = t+1),$$

(12)

where $x_m^n$ denotes the estimated motion magnitude, based on the KLT tracker. The reward matrix uses negative rewards between
frames with high-motion. The flow matrix aggregates the motion magnitude scores for neighboring frames in the summary. This component is inspired by the pre-segmentation criterion used by [5].

**Beat Cuts.** A final consideration is the placement of cuts in the summary with respect to the music track. We believe that cuts should be placed on the beat of the music, as illustrated in Fig. 5. Therefore we reward beat cuts with the following QAP:

\[
p_{BC}^m(n, m) = \delta(m > n + 1),
\]

\[
p_{BC}^s(s, t) = \delta(s = t + 1) \delta(s \in B),
\]

where \( B \) denotes the set of summary slots matching a beat. The reward matrix returns a one, if and only if the frames in are not neighboring in the source video, and \( F \) aggregates these scores only when there is a beat.

### 2.4 Greedy search

The search space, for a summary of \( S \) frames, from a source video with \( N \) frames, is huge, even though we constrain the search space to a forward selection process only. Consider a 5 minute source video (\( N = 9000 \)) and a 30 seconds summary (\( S = 900 \)), for the first frame we can select \( (N-S) \) frames, the second frame is then selected from \( (N-f_1-S-1) \), i.e. pick any frame between the previous selected frames and the \( S-1 \) last frames, etc. This is in the order of \( O(N!/(N-S)!)) \), and yield billions of possible permutations. As said before, for a general QAP (or its \( \epsilon \)-approximate solution) there exist no efficiently optimal solution. Therefore we resort to a greedy search which selects one frame at the time.

Given a partial permutation \( P_g \), consisting of the permutation of the first \( g \) summary frames, we add the next frame \( P_{g+1} = t \). We select the best frame \( t \), based on the current reward and an approximation of the (expected) future rewards. We approximate the future rewards of frame \( t \), by evaluating Eq. (2) with the partial permutation when adding frames \( t, t+1, t+2, \ldots \) consecutively to the summary, to the manifestation of the next 1 to 4 beats. This yields per frame \( t \) four scores, which we normalize for their different lengths, and we select the frame with the highest score. We call our approximation the beat-look-ahead score.

To further reduce the search we (1) require each segment to last at least one second, i.e. for a new segment the next 25 frames are also added, this is identical to adding a reward of \(-\infty\) on segments shorter than \( l_m = 25 \); and (2) consider only frames in a small window around the previous selected frame, if \( p_g = v \), then frame \( t \) is selected from \( v+1 \leq t \leq v + \frac{N}{5} \). This window size is based on preliminary experiments.

### 3 EXPERIMENTS

In this section we experimentally validate our proposed methods. First, we describe the experimental setup. Then, we present visual-only summarization results to compare to recent work. Finally, we present the results of our music-guided video summarization.

#### 3.1 Dataset and experimental setup

**SumMe dataset** [5]. For all experiments we use the recently introduced SumMe dataset, which contains 25 amateur-shot raw videos (40-400 seconds) covering holiday moments, events and sports. The videos are illustrated in Fig. 6. For each video, 15-18 human participants have been asked to create a video summary of 5-15% of the original length. The diversity of the videos and the availability of multiple annotations make the dataset perfectly suited for illustrating performance of our summarization methods.

**Evaluation.** To evaluate a video summarization we use the provided human summaries. First, we compute precision and recall of frames between a generated summary and a human summary, and use the F1-score to balance precision and recall. To incorporate the fact that summaries are highly subjective, we follow [6] and use the highest F1 score between an automatically generated summary and any of the human summaries, we denote this as the **Best F1** score. It ensures that the generated summary is rewarded if it matches closely to one of the human annotators.
**Table 1:** Comparison to state-of-the-art. Methods indicated with * use the same features. Our QAP model allows to directly use frame-based interestingness prediction, without resorting to pre-segmentation methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>F1</th>
<th>Recall</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>16.8</td>
<td>17.5</td>
<td>16.6</td>
</tr>
<tr>
<td>Uniform</td>
<td>27.1</td>
<td>29.4</td>
<td>25.1</td>
</tr>
<tr>
<td>Gygli et. al. [5]</td>
<td>39.3</td>
<td>44.4</td>
<td>35.3</td>
</tr>
<tr>
<td>Gygli et. al. [6]</td>
<td>39.7</td>
<td>43.0</td>
<td>36.8</td>
</tr>
<tr>
<td>Single Frames*</td>
<td>34.7</td>
<td>38.4</td>
<td>33.5</td>
</tr>
<tr>
<td>Super Frames* [5]</td>
<td>36.4</td>
<td>40.4</td>
<td>34.2</td>
</tr>
<tr>
<td>QAP Model*</td>
<td>38.3</td>
<td>42.4</td>
<td>36.6</td>
</tr>
</tbody>
</table>

*Interestingness Features.* For the interestingness prediction, we use a subset of the features used in [5]. This is a collection of features modeling *attention*, using spatial and temporal salience [3, 7]; and modelling *aesthetics*, based on colourfulness, contrast, and distribution of edges [1, 8]. The other features used in [5], a.o. landmark detection and person detection, were not reproducible, and therefore not used in our experiments.

We extend this collection of features, with a high-level frame description based on ImageNet objects [2]. In order to do so, we extract per frame the penultimate layer of the deep network, provided by [15]. This is a 1024 dimensional feature, which we reduce to 64 dimensions using PCA, so that we can learn both the unary and pairwise terms in the interestingness prediction.

We learn the parameters \( w \) of Eq. (3), by random sampling 100 frames from each video in the dataset and train a predictor. The final model is an average over 50 repetitions of this training.

### 3.2 Visual-only Summaries

**Tuning summarization components.** In a set of preliminary results, we tune the weights, used in Eq. (2), of each component. Starting with an equal weighting \((w_c : w_o = 1)\), we tune the components one by one. For each component, we use leave-one-out performance to vote for a specific parameter value, and the value with the highest number of votes is selected. Since parameters interact, repeating this search could result in different weight values. The obtained weights are: \( I = 1, MB = 2, SL = 1 \), and \( U = \frac{1}{2} \).

**Experimental results.** The goal of this experiment is to see whether the QAP model is able to generate high quality summarizations without the need for pre-segmentation methods. We compare our QAP model with current state-of-the-art methods on this dataset and we add a model based on *Single Frame* interestingness predictions and on the *Super Frames* pre-segmentation used in [5]. The latter methods use exactly the same raw interestingness predictions, which makes them comparable.

The results are presented in Table 1. We observe that any of the computational methods outperform random or uniform segmentation. Furthermore we observe that our implementation of [5] results, we tune the weights, used in Eq. (2), of each component. Starting with an equal weighting \((w_c : w_o = 1)\), we tune the components one by one. For each component, we use leave-one-out performance to vote for a specific parameter value, and the value with the highest number of votes is selected. Since parameters interact, repeating this search could result in different weight values. The obtained weights are: \( I = 1, MB = 2, SL = 1 \), and \( U = \frac{1}{2} \).

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Table 2: Per video results on the SumMe dataset using the Best F1 measure, comparing visual-only methods against audio-guided methods. (*) Average on-beat cuts over all songs (for QAP). Surprisingly, the audio-guided methods outperform the visual-only methods by up to 6% absolute performance when an oracle could provide the most suited audio-track per video.

First, we observe that our music-guided methods, surprisingly, obtain better results than any of visual-only methods, even better than the state-of-the-art summarization method of [6] (39.7%, see Table 1). Our results are also better than the recent work of [22], where 38.6% is reported using slightly different evaluation settings and on par with their method that uses extensive additional labeled data to train interestness and hyper-parameters (41.8%). Further, the relatively stable average Best F1 for the different music-tracks, indicate that the weighting of the components is not music-track specific per se. Still the large variation in performance between different models for a specific video, indicate that the relative importance of model components vary. Finally, when we compare statistics about the cuts in the video summary, it is apparent that the no-music QAP model generates more cuts, and have hardly any aligned with the audio (averaged over all songs), while the music guided model has almost all cuts aligned with music. In conclusion, the music guidance (in audio-visual match and beat cuts), enables to generate higher quality video summarizations.

In Fig. 7 we show the selection of frames for the QAP-AV model for different soundtracks for three different videos, and as reference show the average human summary selection. Video examples are included in the supplementary material.

4 CONCLUSION

In this paper we have introduced a model for music-guided video summarization, which we have modeled as a quadratic assignment problem (QAP). The QAP formulation allows to dynamically create video segments, match the music-dynamics, have boundaries with low motion, and with cuts (mostly) on the beat of a provided music-track. Experimentally we have validated our approach on the SumMe dataset, showing that our QAP model is on par with current state-of-the-art video summarization and that our music-guided models even outperform these. In conclusion our QAP model yields high quality summaries (in terms of F1), which are also more appealing to watch (see examples in supplementary material).

For future work, we aim to extend our method to exploit the audio track of the source video as input modality, to allow for repetitions (e.g. for the chorus of a song), and to include basic video effects (panning, crop, zoom, speed-up and slowmotion). This will search the limits of the QAP, since rewards for these effects require higher-order dependencies than only neighboring dependencies, which could be based either on parametrized flow and reward matrices, or by another search strategy to evaluate permutations.
REFERENCES


