

Lyric Video Analysis Using Text Detection and Tracking

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Abstract. We attempt to recognize and track lyric words in lyric videos. Lyric video is a music video showing the lyric words of a song. The main characteristic of lyric videos is that the lyric words are shown at frames synchronously with the music. The difficulty of recognizing and tracking the lyric words is that (1) the words are often decorated and geometrically distorted and (2) the words move arbitrarily and drastically in the video frame. The purpose of this paper is to analyze the motion of the lyric words in lyric videos, as the first step of automatic lyric video generation. In order to analyze the motion of lyric words, we first apply a state-of-the-art scene text detector and recognizer to each video frame. Then, lyric-frame matching is performed to establish the optimal correspondence between lyric words and the frames. After fixing the motion trajectories of individual lyric words from correspondence, we analyze the trajectories of the lyric words by k-medoids clustering and dynamic time warping (DTW).

Keywords: Lyric video \cdot Lyric word tracking \cdot Text motion analysis \cdot Video design analysis

1 Introduction

The targets of document analysis systems are expanding because of the diversity of recent document modalities. Scanned paper documents only with texts printed in ordinary fonts were traditional targets of the systems. However, recent advanced camera-based OCR technologies allow us to analyze arbitrary images and extract text information from them. In other words, we can now treat arbitrary images with text information as documents.

In fact, we can consider videos as a promising target of document analysis systems. There have already been many attempts to analyze videos as documents [1]. The most typical attempt is caption detection and recognition in video frames. Another attempt is the analysis of the video from the in-vehicle camera. By recognizing the texts in the in-vehicle videos, it is possible to collect store



Fig. 1. Frame image examples from lyric video.

and building names and signboard information around the road automatically. There was also an attempt (e.g., [2] as a classical trial) to recognize the sport player's jersey number for identifying individual players and then analyzing their performance.

In this paper, we use *lyric videos* as a new target of document analysis. Lyric videos are music videos published at internet video services, such as YouTube, for promoting a song. The main characteristic of lyric videos is that they show the lyric words of the song (almost) synchronously to the music. Figure 1 shows several frame examples from lyric videos. Lyric words are often printed in various decorated fonts and distorted by elaborated visual designs; they, therefore, are sometimes hard to read even for humans. Background images of the frames are photographic images or illustrations or their mixtures and often too complex to read the lyrics. This means that lyric word detection and recognition for lyric videos is a difficult task even for state-of-the-art scene text detectors and recognizers.

In addition, lyric words in lyric videos move very differently from words in ordinary videos. For example, lyric words often move along with arbitrarilyshaped trajectories while rotating and scaling. This property is very different from video captions since they do not move or just scroll in video frames. It is also different from scene texts in videos from the in-vehicle camera; scene texts move passively according to camera motion, whereas lyric words move actively and arbitrarily. In fact, lyric words and their motion are designed carefully by the creator of the lyric video so that the motion makes the video more impressive. To give a strong impression, lyric words might move like an explosion.



Fig. 2. Our lyric video analysis task. After detecting and recognizing words in video frames, the words in the lyric are tracked over frames. Finally, the word motion trajectories are classified into several clusters to understand the trends of lyric word motions.

The purpose of this paper is to analyze the motion of the lyric words in lyric videos. Specifically, we try to extract and track words in the lyric words automatically and then group (i.e., clustering) their motions into several types to understand their trends. Nowadays, anyone can post her/his music with video. This research will contribute to those non-professional creators to design their own lyric videos. In the future, it will also be possible to realize automatic lyric video generation, by extending this work to understand the relationship between lyric word motion and music beat or music style.

For the above purpose, we develop a lyric word detection and tracking method, where lyric information is fully utilized. As noted before, lyric words are heavily decorated and shown on various background images. Even stateof-the-art scene text detectors and recognizers will have miss-detections (falsenegatives), false-detections (false-positives), and erroneous word recognition results. We, therefore, utilize the lyric information as metadata for improving detection and tracking performance. As shown in Fig. 2, we first apply state-ofthe-art scene text detectors and recognizers to each video frame. Then, dynamic programming-based optimization is applied to determine the optimal matching between the video frame sequence and the lyric word sequence. We call this novel technique *lyric-frame matching*. Then, using the lyric-frame matching result as a reliable correspondence, spatio-temporal search (tracking and interpolation) is performed for fixing the motion trajectory of each lyric word.

The main contributions of this paper are summarized as follows:

 First, to the authors' best knowledge, this is the first trial of detecting and then tracking lyric words in lyric videos.

- Second, we propose a lyric-frame matching technique where lyric information of the target music is fully utilized as metadata for accurately determining the most confident frame where a lyric word appears. Dynamic programming and state-of-the-art text detection and recognition techniques are used as the modules of the proposed technique.
- Third, we prepared a dataset comprised of 100 lyric videos and attached ground-truth (bounding boxes for lyric words) manually at 10 frames for each of 100 videos. This effort enables us to make a quantitative evaluation of our detection and tracking results.
- Fourth, as an analysis of lyric word motions, we grouped them into several representative word motions by k-medoid clustering. From the clustering result, we could represent each lyric video by a histogram of representative motions.

2 Related Work

To the authors' best knowledge, this paper is the first trial of analyzing lyric videos as a new document modality. We, however, still can find several related tasks, that is, video caption detection and recognition, and text tracking. In the following, we review the past attempts on those tasks, although the readers also refer to a comprehensive survey [1,3]. It should be noted that the performance on all those tasks has drastically been improved by the recent progress of scene text detection and recognition technologies. Since the attempts on scene text detection and recognition are so huge (even if we limit them only to the recent ones), we will not make any review on the topic. A survey [3] will give its good overview.

Caption detection and recognition is a classical but still hot topic of document image analysis research. Captions are defined as the texts superimposed on video frames. Captions, therefore, have different characteristics from scene texts. We can find many attempts on this task, such as [4-13]. Most of them deal with the static captions (i.e., captions without motions), while Zedan [10] deals with moving captions; they assume the vertical or horizontal scrolling of caption text, in addition to the static captions.

Rather recently, scene text tracking and video text tracking [14–22] have also been tried, as reviewed in [1]. Each method introduces its own word tracker. For example, Yang [19] uses a dynamic programming-based tracker to have an optimal spatio-temporal trajectory for each word. A common assumption underlying those attempts is that text motions in video frames are caused mainly by camera motion. Therefore, for example, neighboring words will move to similar directions. We also find "moving MNIST" [23] for a video prediction task, but it just deals with synthetic videos capturing two digits are moving around on a uniform background.

Our trial is very different from those past attempts at the following three points at least. First, our target texts move far more dynamically than the texts that the past attempts assume. In fact, we cannot make any assumption on the location, appearance, and motion of the words. Second, our trial can utilize the lyric information as the reliable guide of text tracking and therefore we newly propose a lyric-frame matching technique for our task. Third, our main focus is to analyze the text motion trajectory from a viewpoint of video design analysis, which is totally ignored in the past text tracking attempts.

3 Lyric Video Dataset

We collected 100 lyric videos according to the following steps. First, a list of lyric videos is generated by searching YouTube with the keyword "official lyric video"¹. The keyword "official" was added not only for finding videos with long-term availability and but also for finding videos created by professional creators. Videos on the list were then checked visually. A video only with static lyric words (i.e., a video whose lyric words do not move) is removed from the list. Finally, the top-100 videos on the list are selected as our targets².

The collected 100 lyric videos have the following statistics. Each video is comprised of 5,471 frames (3 min 38 s) on average, 8,629 frames (5 min 44 s) at maximum, and 2,280 frames (2 min 33 s) at minimum. The frame image size is $1,920 \times 1,080$ pixels. The frame rate is 12, 24, 25, and 30 fps on 1, 58, 25, and 16 videos, respectively. The lyrics are basically in English. Each song is comprised of 338 lyric words on average, 690 words at maximum, and 113 at minimum.

Figure 3 shows four examples showing the variations of the number of lyric words in a frame. Figure 3 (a) shows a typical frame with lyric words. It is quite often in lyric videos that a phrase (i.e., consecutive lyric words) is shown over several frames. It is rather rare that only a single lyric word is shown in a one-by-one manner synchronously with the music. We also have frames without any lyric word, like (b). Those frames are often found in introduction parts, interlude parts, and ending parts of lyric videos. Figures 3 (c) and (d) contain many words in a frame. In (c), the same word is repeatedly shown in a frame like a refrain of a song. The words in (d) are just decorations (i.e., they belong to the background) and not relating to the lyrics.

For a quantitative evaluation in our experiment, we attach the bounding boxes for lyric words manually at 10 frames for each lyric video. The 10 frames were selected as follows; for each video, we picked up frames every three seconds and then select 10 frames with the most word candidates detected automatically by the procedure of Sect. 4.1. The three-second interval is necessary to avoid the selection of the consecutive frames. If a lyric word appears multiple times in a frame (like Fig. 3 (c)), the bounding box is attached to each of them. For the rotated lyric words, we attached a non-horizontal bounding box³. Consequently, we have $10 \times 100 = 1,000$ ground-truthed frames with 7,770 word bounding boxes for the dataset.

¹ The search was performed on 18th July 2019.

² For the URL list of all the videos and their annotation data, please refer to https://github.com/uchidalab/Lyric-Video.

³ To attach non-horizontal bounding boxes, we used the labeling tool roLabelImg at https://github.com/cgvict/roLabelImg.



(c) Duplicated lyric words (like refrains).

KE

LING

 \mathbf{F}



(b) No lyric word (interlude).



(d) Words unrelated to the lyrics.

Fig. 3. Variations of the spatial distribution of lyric words in a video frame.

4 Lyric Word Detection and Tracking by Using Lyric Information

In this section, we will introduce the methodology to detect and track lyric words in a lyric video. The technical highlight of the methodology is to fully utilize the lyric information (i.e., the lyric word sequence of the song) for accurate tracking results. Note that it is assumed that the lyric word sequence is provided for each lyric video as metadata.

4.1 Lyric Word Candidate Detection

As the first step, lyric word candidates are detected by scene text detectors, as shown in the left side of Fig. 4 (a). Specifically, we use two pretrained state-of-theart detectors, PSENet [24] and CRAFT [25]. Then, each detected bounding box is fed to a state-of-the-art scene text recognizer; we used TPS-Resnet-BiLSTM-Attn, which achieved the best performance in [26]. If two bounding boxes from those two detectors have 50% overlap and the same recognition result, they are treated as the duplicated bounding boxes and thus one box is removed from the later process.

4.2 Lyric-Frame Matching

After the detection, lyric-frame matching is performed to find the correspondence between the given lyric word sequence and the frame sequence. The red path on the right side of Fig. 4 (a) shows the matching path showing the optimal correspondence. Assume the video and its lyrics are comprised of T frames and K words, respectively, and $t \in [1, T]$ and $k \in [1, K]$ are their indices, respectively. If the path goes through the node (k, t), the frame t is determined as the most confident frame for the kth lyric word. Note that the other frames where the same kth lyric word appears will be determined later by the tracking process of Sect. 4.3.

The path is determined by evaluating the distance D(k,t) between the kth word and the frame t. The circled number in Fig. 4 (a) represents D(k,t). A



(d) Tracking result of "you" and "ever".

Fig. 4. The detail of lyric word detection and tracking. (Color figure online)

smaller value of D(k,t) means that the kth lyric word will be found at t with a high probability. The distance is calculated as $D(k,t) = \min_{b \in B_t} d(k,b)$, where B_t is the set of bounding boxes (i.e., words) detected at t and d(k,b) is the edit distance function between the kth lyric word and the bth detected word at t. If D(k,t) = 0, the kth lyric word is correctly detected at t without misrecognition.

With the distance $\{D(k,t)|\forall k,\forall t\}$, the globally optimal lyric-frame matching is obtained efficiently by dynamic programming (DP), as the red path of Fig. 4 (a). In the algorithm (so-called the DTW algorithm), the following DP recursion is calculated at each (k,t) from (k,t) = (1,1) to (K,T);

$$g(k,t) = D(k,t) + \min_{t-\Delta \le t' < t} g(k-1,t'),$$

where g(k,t) becomes the minimum accumulated distance from (1,1) to (k,t). The parameter Δ specifies the maximum skipped frames on the path. In the later experiment, we set $\Delta = 1,000$ and it means that we allow about 40-s skip for videos with 24 fps. The computational complexity of the DTW algorithm is $O(\Delta TK)$.

It should be emphasized that this lyric-frame matching process with the lyric information is mandatory for lyric videos. For example, the word "the" will appear in the lyric text many times; this means that there is a large ambiguity of the spatio-temporal location of a certain "the". We, therefore, need to fully utilize the sequential nature of not only video frames but also lyric words by the lyric-frame matching process for determining the most confident frame for each lyric word.

4.3 Tracking of Individual Lyric Words

Although the kth lyric word is matched only to a single frame t by the above lyric-frame matching step, the word will also appear in the neighboring frames of t. We, therefore, search those frames around the tth frame, as shown in Fig. 4 (b). This search is simply done by evaluating not only spatio-temporal similarity but also word similarity to the kth word, at the neighboring frames of t. If both similarities are larger than thresholds at t', we assume the same kth word is also found at t'.

Finally, an interpolation process, shown in Fig. 4 (c), is performed for completing the spatio-temporal tracking process of each lyric word. By the above simple searching process, the lyric word will be missed at a certain frame when a severe misrecognition and/or occlusion occurs on the word at the frame. In the example of Fig. 4, the third lyric word "THOUGHT" is determined at the fifth frame by the lyric-frame matching process and then found at the third and sixth frames by the search. However, it was not found at the fourth frame due to a severe misrecognition of the word. If such a missed frame is found, the polynomial interpolation process determines the location of the lyric word at the frame. Figure 4 (d) shows the final result of the tracking process for two lyric words "you" and "ever."



(c) Motion by rotating.

Fig. 5. Successful results of lyric word detection and tracking under variable motion types.

5 Experimental Results

By applying the proposed method to all frames of the collected 100 lyric videos (about 547,100 frames in total), we had the tracking results for all lyric words (about 33,800 words in total).

5.1 Qualitative Evaluation

Figure 5 shows several successful results of lyric word detection and tracking. In (a), the word "DON'T", which moves horizontally, is tracked successfully. The words "LET" and "HIM" in (a) and all the words in (b) are tracked correctly, although their size varies. The words in (c) are also tracked successfully even under frame-by-frame rotation.



Fig. 6. The effect of lyric information. Top: The initial word detection results shown as green boxes. Bottom: The final tracking result shown as blue boxes. The lyric words in those frames are "well be alright this time". (Color figure online)



(b) Tracking error due to multiple appearances of the same word ("BROKEN").

Fig. 7. Failure results of lyric word detection and tracking.

Figure 6 confirms the effect of using lyric information at the lyric-frame matching process and the following tracking process for accuracy improvement. Since these frames have a complex background (with character-like patterns), unnecessary bounding boxes are found by the initial word detection step. In contrast, only the correct lyric words remain after lyric-frame matching and tracking.

Figure 7 shows typical failure cases. The failure of (a) was caused by a heavy distortion on a word by an elaborated visual design of the video. Specifically, the word "CAST" is always partially occluded and never detected and recognized correctly over frames. Lyric videos frequently show words which are difficult to read even by the state-of-the-art word detectors and recognizers (and also

Table 1.	Performance	of the lyri	c word	detection	and	tracking.	MA:	Lyric-frame
matching.	TR: Tracking	g. IN: Interp	olation	. TP: #Tr	ue-po	ositive. FF	P: #Fa	alse-positive.
FN: #Fals	se-negative. P:	Precision	(%). R:	Recall $(\%)$). F:	F-measure	e.	

MA	TR	IN	ΤР	\mathbf{FP}	FN	$P = \frac{TP}{TP+FP}$	$R = \frac{TP}{TP+FN}$	$F = \frac{2PR}{P+R}$
\checkmark			72	12	$7,\!698$	85.71	0.93	0.0183
\checkmark	\checkmark		5,513	462	$2,\!257$	92.27	70.95	0.8022
\checkmark	\checkmark	\checkmark	$5,\!547$	550	2,223	90.98	71.39	0.8000

by a human). The failure of (b) is caused by a refrain of the same word in the lyrics. Especially in musical lyrics, it is very frequent that the same word appears repeatedly within a short period. These multiple appearances easily distract our tracking process.

5.2 Quantitative Evaluation

Table 1 shows the quantitative evaluation result of the performance of the lyric word detection and tracking, by using 1,000 ground-truthed frames. If a bounding box of a lyric word by the proposed method and the ground-truth bounding box of the same lyric word have IoU > 0.5, the detected box is counted as a successful result. If multiple detected boxes have an overlap with the same ground-truth box with IoU > 0.5, the detected box with the highest IoU is counted as a true-positive and the remaining are false-positives.

The evaluation result shows that the precision is 90.98% and therefore the false positives are suppressed successfully by the proposed method with the lyric-frame matching step and the later tracking step. The interpolation step could increase TPs as expected, but, unfortunately, also increases FPs and slightly degrades the precision value.

The recall is about 71% at the best setup⁴. There are several reasons that degrade recall. First, as shown in Fig. 7 (a), the elaborated visual design often disturbs the word detection and recognition process and degrades the recall. In other words, we need to develop new text detectors and recognizers that are robust to the visual disturbances to the words in lyric videos as future work.

The second reason for the low recall is the errors at the lyric-frame matching step. Since our lyric-frame matching allows the skip of $\Delta = 1,000$ frames (about 40 s) at maximum, to deal with frames without lyrics (interlude). This sometimes causes a wrong skip of the frames where lyric words actually appear and induce errors in the matching step. Multiple appearances of the same word (such as "I") also induce matching errors.

The third reason is the deviation from the official lyrics; even in the official lyric videos, the lyrics shown in video frames are sometimes different from the official lyrics due to, for example, the improvisation of the singer. Since we believe

 $^{^4}$ As explained before, only a single frame is determined for each lyric word by the lyric-frame matching. This results in very low recall (0.93%).



Fig. 8. The mean word motion histograms of four video clusters. Each of 60 bins corresponds to a representative word motion. " $11\sim20$ " means the 10 representative motions for the trajectories with $11\sim20$ frame length. At the right side, the distribution of the 100 histograms of the individual videos is visualized by tSNE.

the official lyrics for lyric-frame matching, such deviations disturb the matching process and cause the degradation of recall.

5.3 Text Motion Analysis by Clustering

Finally, we analyze the motion trajectory of lyric words. As the result of the proposed lyric word detection and tracking process, we already have the motion trajectory of individual lyric words. Trend analysis of those trajectories will give a hint about how to design lyric videos. Note that we consider that the trajectories subjected to this analysis are reliable enough because the quantitative evaluation in Sect. 5.2 shows a high precision.

As the motion trajectory analysis, we first determine representative motion trajectories via simple clustering. Before the clustering, we divide them into six subsets by their length (11~20 frames (4336 trajectories), 21~30 (4293), 31~40 (3797), 41~50 (3159), 51~70 (4057), 71~100 (2660)). Note that 6123 extremely short (≤ 10) and 2469 extremely long (>100) trajectories are excluded from the analysis. Then for each subset, we performed k-medoid clustering with DTW distances between trajectories. We set k = 10 and thus we have 60 representative motions.

Using those 60 representative motions, we create a histogram with 60 bins for each lyric video. Specifically, like a bag-of-words, all word trajectories in the video are classified into one of 60 representative motions and then we have a histogram whose qth bin represents the number of the lyric words whose motion is the most similar to the qth representative motion. All histograms are then normalized to have the same number of votes.

After this histogram-based representation of all videos, we perform another clustering (k-means) in order to classify 100 videos into clusters with similar word motions. According to the Calinski-Harabasz criterion, we have 4 clusters. Figure 8 shows the mean histogram of those clusters. This means that our 100 lyric videos can be classified into four types and each of them contains the lyric words whose motion trend is described by the corresponding histogram. Among 100 videos, 55 belong to (a), 11 to (b), 25 to (c), and 9 to (d).

In all the histograms, prominent peaks are found at #1, #12, #27, #37, and #58 and all of those five representative motions are static motion (with different frame lengths). This indicates that most lyric words are static. With a closer inspection, we can find the ratios of the five representative motions are different in each histogram. This indicates that the period of showing a word (without motion) is different by the tempo of the music. For example, (c) has many words displayed only for a very short (11~20) period.

Another prominent peak is found at #43 and this represents a horizontal motion. It is interesting to note that a peak at horizontal motions is only found at $51\sim70$; this means that speed of the frequent horizontal motions is almost constant regardless of lyric videos (and also regardless of their tempo). Another observation is that a video that belongs to (a) will contain wide motion varieties. For example, the #51 representative motion is a circular motion.

6 Conclusion and Future Work

To the authors' best knowledge, this paper is the first trial of analyzing lyric videos as novel and dynamic documents. For this difficult analysis task, we developed a novel technique, called lyric-frame matching, where the temporal location, i.e., the frame, of each word in the lyrics is determined automatically by dynamic programming-based optimization. We experimentally showed that the combination of the lyric-frame matching technique and several state-of-the-art word detectors and recognizers could detect lyric words with more than 90% precision and 70% recall on our original 100 official lyric video dataset. Although the recall is lower than the precision, the current tracking performance is already reliable for analyzing the motion trajectories of lyric words for understanding the text motion design in lyric videos. In fact, we could determine four typical motion patterns of lyric videos for our 100 videos.

Since this is the first trial of lyric video analysis, we have multiple future works. First, word detection and recognition performance should be improved for lyric videos. Since the distortions (including elaborated visual designs) on lyric texts are often very different from those of scene texts. This means it is still insufficient to apply state-of-the-art scene text detectors and recognizers to this task. The second and more important future work is to analyze word motion trajectories in lyric videos. Since the moving words in lyric videos are a new target of document analysis, we need to develop many analysis schemes. Word motion analysis for each music genre is straightforward. A more important analysis scheme is the correlation analysis between word motion and music signals, i.e., sounds. We often observe that word motions are strongly affected by the beat and mood of the music. Our final goal is to generate lyric videos automatically or semi-automatically from lyric information and music signals, based on those technologies and analyses. For example, our motion trajectory analysis could contribute to enabling data-driven motion styles on a tool for creating lyric videos [27].

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Videos Shown in the Figures

In the figures of this paper, the following video frames are shown. For URL, the common prefix part "https://www.youtube.com/watch?v=" is omitted in the list. Note that the URL list of all 100 videos and their annotation data can be found at https://github.com/uchidalab/Lyric-Video.

- Fig. 1: (a) MK, 17, NoBAfjvhj7o; (b) Demi Lovato, Really Don't Care, EOEeN9NmyU8; (c) Alok, Felix Jaehn & The Vamps, All The Lies, oc218bqEbAA; (d) Taylor Swift, Look What You Made Me Do, 3KORzZGpyds; Eig 2: Bein Schulz Sugar iDUSA LeVGY
- Fig. 2: Robin Schulz, Sugar, jPW5A_JyXCY.
- Fig. 3: (a) Marshmello x Kane Brown, One Thing Right, 06RyKbcpBfw; (b) Harris J, I Promise, PxN6X6FevFw; (c) Rita Ora, Your Song, i95Nlb7kiPo; (d) Green Day, Too Dumb to Die, qh7QJ_jLam0;
- Fig. 4: Freya Ridings, Castles, pL32uHAiHgU.
- Fig. 5: (a) Dua Lipa, New Rules, AyWsHs5QdiY; (b) Anne-Marie, Then, x90JpU70_cU; (c) Imagine Dragons, Bad Liar, uEDhGX-UTeI;
- Fig. 6: Ed Sheeran, Perfect, iKzRIweSBLA;
- Fig. 7: (a) Imagine Dragons, Natural, V5M2WZiAy6k; (b) Kelly Clarkson, Broken & Beautiful, 618gyacUq4w;

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