Event Detection based on Twitter Enthusiasm Degree for Generating a Sports Highlight Video

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ABSTRACT

This paper presents a Twitter-based event detection method based on "Twitter Enthusiasm Degrees (TED)" toward generating a highlight video of a sports game. Existing methods not only depend on both languages and sports types but also often falsely detect non-target events. In contrast, the proposed method detects sports events using TEDs calculated from several kinds of string features independent of languages and sports. We applied the proposed method to actual sports games, and compared the detected events with the events present in broadcasted highlight videos, and confirmed the effectiveness and the language and sports type independencies of the proposed method.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

Keywords

Social media; sports video; highlight; event detection

1. INTRODUCTION

The techniques for automatic summarization of broadcast videos are becoming more important in recent years. Among various kinds of broadcast videos, summarizing sports game videos is more important because some sports games last for a long duration [1]. When summarizing a sports game video, we should take into account the viewpoint of the viewers so as to let them understand not only the game flow but also the atmosphere of the game such as the excitement at each event of the game. We here call such a summarized video a "highlight video". The viewers are excited by events such as a goal, a play that assists a goal and a goal-scoring opportunity, because they are closely related to the winning or the losing of a game. In this paper, we focus on automatic detection of such kinds of events from a sports game in order to generate its highlight video.

As an information source for detecting such events from a sports game, we make use of Twitter that is currently the most popular micro-blogging service. The number of active Twitter users was more than 140 million by March, 2012 and is increasing afterwards [2]. The biggest advantage of using Twitter for our research purpose is that it provides instantaneous information. That is, Twitter users who are watching a sports game can post their messages called "tweets" in real-time as shown in Table 1. Viewers from various countries tweet their feelings (excitement or disappointment) at each event in various languages within 140 characters. Twitter also has functions for interactions with others. For example, the function "retweet" enables Twitter users to easily repost someone else's tweet. In addition, "hashtags" indicated by keywords or phrases prefixed with the symbol "#" can be added in a tweet in order to categorize the message. This function helps users to easily search tweets on a specific topic, to find users who have common interests, and so on. Furthermore, Twitter Inc. provides the Twitter Streaming

Table 1: Examples of tweets on the London Olympic women's soccer final: Japan vs. USA.

Posted time	Tweets
19:55:07 UTC−6	GOOOOOOOOOOOOOOOOOAA AAAAAAAAALLLLLLLLLLL!!!
19:55:08 UTC−8	Go #TeamUSA!
19:55:10 UTC+2	US. leads Japan 1-0 at halftime in gold medal women's soccer match.
19:55:12 UTC+9	うあああああああああああ 切り替えの遅さが目立つなぁ
19:55:15 UTC−5	GOAL #TEAMUSA !!!!!!!!!!! Up 2:0 in the 55th Minutes!!!

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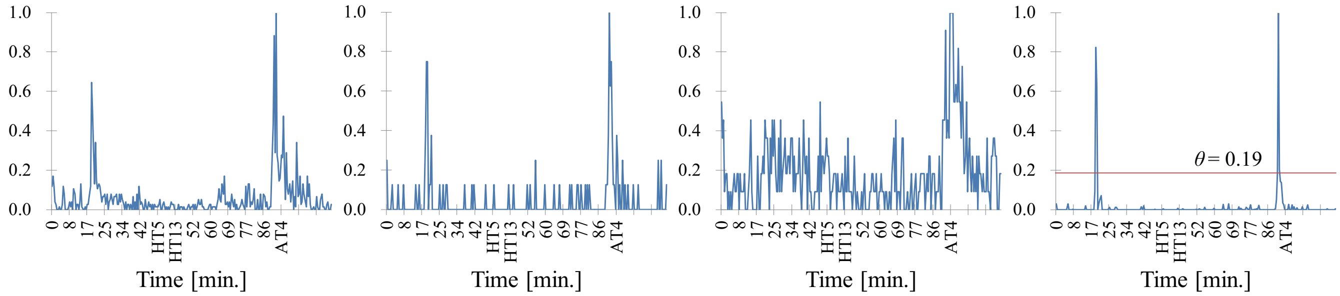


(a) Feature value: E (b) Feature value: L (c) Feature value: R (d) TED

Figure 1: Example of the feature values (E, L and R) and the TED calculated by the proposed method for the UEFA EURO2012 quarterfinal: Spain vs. France (Spain scored in the 19th minute of the first half, and added a goal by a penalty kick in the 1st minute of the second-half additional time (AT1)).

API. We can collect tweets posted during the target game by using these functions and APIs.

Focusing on the relationship between Twitter and sports, some Twitter-based methods for summarizing a sports video have been proposed [3, 4]. These methods can accurately recognize events in a sports video by analyzing the phrases in Twitter tweets. This approach, however, not only requires a list of phrases specific to the target sports but also highly depends on the language of the tweets. In addition, although these methods detect events based on the increase or the decrease of the number of tweets, it increases not only at the occurrence of an event but also at the end of an event [5]. Thus, these methods cannot simply be applied to our task to prevent false detection of events where the viewers are not excited.

This paper proposes a method that detects sports events based on a feature named "Twitter Enthusiasm Degree" (TED) which is derived from certain string patterns in tweets. The TED here is calculated by integrating three kinds of features: two kinds of features that express the users' excitement in addition to a feature that represents the end of an event. By this way, without any complex audio and/or video analysis, we expect to generate a highlight video that includes events where the viewers are excited.

Compared with the previous work [3, 4], the contribution of the proposed method is that 1) it does not require a list of phrases according to the target sports and 2) it does not depend on the language of the tweets. As for the scope of application of the proposed method, we target two different types of sports: soccer and baseball. These two sports are different in both the process of scoring and the structure of a game. In addition, many tweets regarding the events in these two types of games should be posted due to their world-wide popularity. Therefore, we confirm both the former and the latter contributions by applying the proposed method to the games of these two sports.

2. PROPOSED METHOD

The proposed method detects events that should be included in a highlight video of a target sports game by calculating and thresholding the Twitter Enthusiasm Degree (TED). A highlight video can be automatically generated by collecting the scenes at all the detected events in the game.

The TED here is defined as follows:

$$\mathrm{TED} \equiv E \times L \times (1 - R), \tag{1}$$

where E is the frequency of exclamation marks, L is the number of tweets including a repeated expression and R is the number of retweets. Here, both E and L are for evaluating the excitement of users, whereas R is for evaluating the end of an event. The TED becomes higher when E and L are higher and R is lower. We assume that events with higher TEDs as those that should be included in a highlight video. Note that each feature value is calculated for a time window of $w = 30$ [sec.] and normalized in the range of [0,1]. As a result, we obtain TEDs in the range of [0,1] for every w [sec.].

We explain below the details of each feature and the threshold for the TED with actually-posted tweets on the UEFA EURO2012 quarterfinal: Spain vs. France (Fig. 1).

2.1 Features for calculating the TED

The features used in the proposed method are as follows.

Frequency of exclamations: E.

The excitements or disappointments of Twitter users watching a sports game appear in their tweets particularly at goal-related events. Thus, we focused on the exclamation mark "!" which is a symbol to express excitement. We assumed that the number of exclamation marks in a tweet reflects the degree of excitement of the user. That is, many exclamation marks in an user's tweet means that he/she is very excited (cf. the last row in Table 1). Such tendency actually can be seen around the goal-scoring events in Fig. 1(a).

Number of tweets using repeated expressions: L.

Characters are often repeated like "GOOOOOOAAAAALLLL!!!" as a way of expressing an user's excitement (cf. the first row in Table 1). The proposed method extracts and counts tweets where a character is repeated multiple times (more than five times in the following experiments). Similarly to the feature value E, the feature value increases around the goal-scoring events in Fig. 1(b).

Number of retweets: R.

As mentioned earlier, the number of tweets increases not only at an event but also just after each event [5]. Since

Table 2: Experimental data.

Game	Date	Match	# of scoring events	Duration	# of tweets
S1 (Soccer)	July 1, 2012	UEFA EURO2012: Final	4	165 min.	410,363
S2 (Soccer)	Dec. 16, 2012	2012 FIFA CWC: Final	1	120 min.	22,075
B1 (Baseball)	Oct. 30, 2012	NPB Japan Series: Third match	10	270 min.	28,979
B2 (Baseball)	Oct. 31 2012	NPB Japan Series: Fourth match	1	270 min.	35,359

Table 3: Experimental results: Comparison of events broadcasted by broadcast stations A, B and C with events detected by the proposed method ("–" indicates that no highlight video was broadcasted).

(a) Numbers of events in Game S1

Event	Broadcast station			Proposed method	
	A	B	C	$\alpha = 2$	$\alpha = 1$
Goal	4	–	–	4	4
Start/End	0	–	–	0	2
Others	0	–	–	0	0

(b) Numbers of events in Game S2

Event	Broadcast station			Proposed method	
	A	B	C	$\alpha = 2$	$\alpha = 1$
Goal	1	–	–	1	1
Start/End	0	–	–	1	1
Others	2	–	–	0	3

(c) Numbers of events in Game B1

Event	Broadcast station			Proposed method	
	A	B	C	$\alpha = 2$	$\alpha = 1$
Score	4	7	8	7	10
Start/End	1	1	1	1	1
Others	0	6	7	1	6

(d) Numbers of events in Game B2

Event	Broadcast station			Proposed method	
	A	B	C	$\alpha = 2$	$\alpha = 1$
Score	1	1	1	1	1
Start/End	1	1	1	1	1
Others	10	2	5	6	12

video sections just after each event should be excluded from a highlight video of a sports game, we try to reduce its effect. Here, we focused on the characteristics of retweets; In order to retweet, a user needs to find a tweet, insert the prefix "RT" into the original tweet, and sometimes add his/her own comment. It is difficult to follow these steps on the exact moment of a goal-scoring event. As a result, retweets are delayed, and consequently posted at or after the end of the event. This means that the end of an event could be detected by using the number of retweets. The number of retweets actually increases just after a goal-scoring event and at the end of the game in Fig. 1(c).

2.2 Threshold for detecting highlights

A threshold θ for TED is determined as follows:

$$\theta = \mu + \alpha \times \sigma, \qquad (2)$$

where μ and σ are the mean and the standard deviation of TEDs in a game, respectively, and α is the parameter for adjusting the threshold θ. Events with higher TEDs than the threshold θ are detected for generating the highlight video of the game. By controlling α, we expect to detect not only goal-scoring events but also exciting events such as a scarce goal-miss or a play that assists a goal. Accordingly, the proposed method can flexibly generate a highlight video of a sports game depending on our needs.

For the game in Fig. 1, the threshold is $\theta = 0.19$ with $\alpha = 2$ as shown in Fig. 1(d). In this case, the TED is over the threshold in the 19th minute of the first half and in the 1st minute of the second-half additional time. These exactly matched with the actual goal-scoring events in the game.

3. EXPERIMENTS

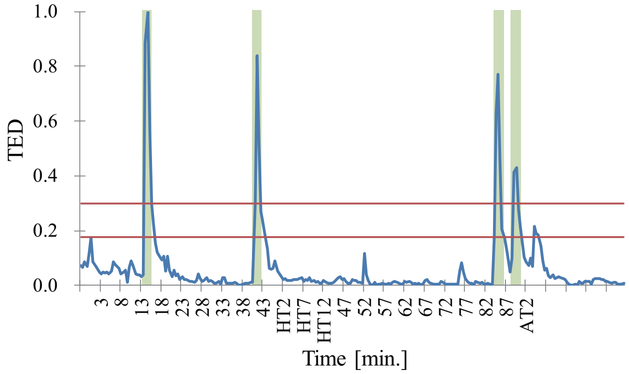
We investigated the effectiveness of the proposed method through the following experiments.

3.1 Method

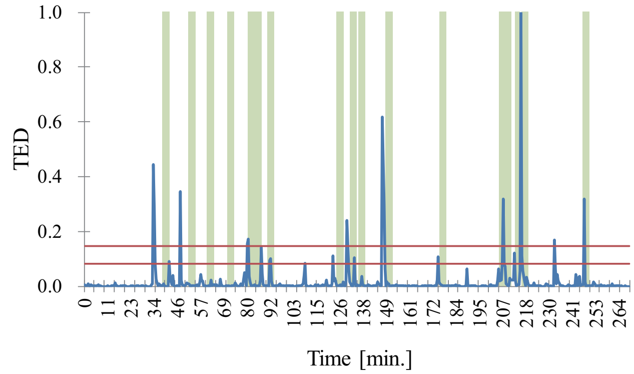
We evaluated the performance of the proposed method by comparing two sets of events: one was detected by the proposed method, and the other was included in the actually-broadcasted highlight video. The experimental data is shown in Table 2. The tweets here were collected by filtering all the tweets posted to Twitter with hashtags: "#euro2012" for Game S1, "#CWD" for Game S2, "#kyojin" and "#lovefighters" for both Games B1 and B2. We used the parameter $\alpha = 2$ or $\alpha = 1$ in Eq. (2) in order to further analize the characteristics of the proposed method in depth.

3.2 Results

Experimental results are shown in Table 3. Each table shows the number of events detected by the proposed method as well as the number of events included in the highlight videos broadcasted by broadcast stations A, B and C. Note that a highlight video was broadcasted only by broadcast station A for Games S1 and S2 as indicated by "–". For reference, Fig. 2 shows examples of the TEDs calculated by the proposed method for Games S1 and B1. As we can see from these results, the proposed method could detect all of the broadcast highlights when $\alpha = 1$. Scoring events are the most important for a sports game and exciting for the viewers of the game. The proposed method also detected other events such as a hit and a fine play. This was because TEDs reflected the viewers' excitement by consecutive hits, viewers' excitement in excaping from a pinch through a fantastic play, and so on. Detecting such events are also important in order to generate a highlight video considering the viewpoint of the viewers. From these results, we confirmed that the proposed method is effective for event detection toward generating a highlight sports video.



(a) Game S1 ("HT" and "AT" represent the half and the additional time, respectively)



(b) Game B1

Figure 2: Example of the calculated TEDs (The colored bars in the background of each graph area indicate the sections included in more than one broadcast highlight videos).

3.3 Discussions

We here discuss the characteristics and the effectiveness of the proposed method based on the experimental results.

Independency to languages and sports types.
We evaluated the performance of the proposed method with multilingual tweets on different types of sports games. The tweets were written in various languages such as English, Japanese, Spanish, and Italian. The proposed method could effectively detect events using such tweets, which shows the language independency of the proposed method. Also, the proposed method could detect events in different types of sports games that are important for generating a highlight video without any modification of its framework. This shows the sports-type independency of the proposed method.

Adequacy in respect of the viewers' viewpoint.
Some events could not be detected by the proposed method, although they were included in the broadcasted highlight videos. One was a less exciting scoring event in the top half of the fifth inning in Game B1 (Fig. 2(b)). That is, runners stood at first and second bases with no out, and then the offensive team got a score via a double play. As a result, the viewers were not excited so much, although it was a scoring event. It would be difficult to detect such an event using the proposed method based on the viewers' enthusiasm. Although such scoring events are important in respect of understanding the game flow, we consider that it was an adequate result in respect of considering the viewers' viewpoint.

Criteria for including events in a highlight video.
The event at the end of Game B1 (Fig. 2(b)) was detected falsely by the proposed method even when $\alpha = 2$, which was not expected. This was because the TED increased by viewers' excitement from the winning / losing. It can be regarded as false detection since the current purpose of this research is to detect events during the game. This result, however, indicates that viewers are excited when the winning or losing is decided. In some cases, it may be better to include such a feverish event into the end of the highlight video of the game. This should be considered as one of our future work.

4. CONCLUSION

This paper presented an event detection method based on a Twitter Enthusiasm Degree (TED) towards generating a highlight video of a sports game. The proposed method calculates TEDs by integrating two features for evaluating the excitement of users and one feature for evaluating the end of an event. Experimental results showed not only the effectiveness of event detection for generating a highlight video but also the independency of the proposed method to languages and sports types. One of the future work is to consider viewers' viewpoint in more depth by analyzing the criteria for including events in a highlight video.

5. REFERENCES

[1] L. Xie, P. Xu, S.-F. Chang, A. Divakaran, and H. Sun. Structure analysis of soccer video with domain knowledge and hidden Markov models. *Pattern Recognition Letters*, 25(7):767–775, May 2008.

[2] Twitter Blog. Twitter turns six. `http://blog.twitter.com/2012/03/twitter-turns-six`. (Feb. 7, 2013).

[3] J. Lanagan and A.F. Smeaton. Using twitter to detect and tag important events in live sports. In *5th AAAI Int'l Conf. on Weblogs and Social Media*, pages 542–545, July 2011.

[4] S. Zhao, L. Zhong, J. Wickramasuriya, and V. Vasudevan. Human as real-time sensors of social and physical events: A case study of twitter and sports games. Technical Report TR0620–2011, Rice University and Motorola Labs, June 2011.

[5] D.A. Shamma, L. Kennedy, and E.F. Churchill. Tweet the debates: Understanding community annotation of uncollected sources. In *1st ACM SIGMM Workshop on Social Media*, pages 3–10, October 2009.