MLB Sports Frames Retrieval Using Color Cipher Similarities

Chiunhsiun Lin, Ching-Hung Su, Hsuan Shu Huang, and Kuo-Chin Fan

Abstract— We present a realistic and fully automatic content-based approach for retrieval MLB sports frames efficiently. Specifically, we present a rule-based method for detecting primary and recurrent scenes in MLB videos (e.g., MLB pitching scenes in baseball). The proposed approach transfers each MLB sports frame to a color cipher using only straightforward 8 rules. Subsequently, we utilize the color ciphers to compare the MLB sports frames, namely color ciphers comparison. We succeed in transferring the MLB sports frames retrieval problem to color ciphers comparison, so the computational complexity is decreased obviously. Our system keeps both advantages of the content based videos retrieval system (similarity-based retrieval) and a text based videos retrieval system (very rapid and mature).

Keywords— Color; Color ciphers comparison, Content based videos retrieval (CBVR), MLB sports frames.

I. Introduction

A huge amount of videos now stored in digital format and can only be searched by keywords on the World Wide Web (e.g., Google or Yahoo) as shown in Fig. 1. It would be impossible to cope with the rise of the world-wide web and the spread of digital information unless those data could be retrieved effectively and efficiently. A video retrieval system is a computer system for browsing, searching and retrieving videos from an enormous database of videos. Unfortunately, most traditional and common methods of videos retrieval methods are text-based methods that utilize some processes of adding metadata such as captioning, keywords, or descriptions to the videos. Subsequently, retrieval can be performed over the annotation words. The major drawback of text-based video retrieval is not all videos can be annotated excellently. Some information of videos cannot be expressed wonderfully as a set of text query terms. Moreover, manual videos annotation is time-consuming, laborious and expensive. Furthermore, the text-based retrieval without good annotation makes them unable to be retrieved. The rapid expanding of videos increases the necessity for videos retrieval. The movie industry is an extensive producer of videos, for example, 328,530 movies representing a sum of 740,803 hours [1]. If we add the broadcast TV videos from millions of TV stations worldwide, and thousands upon thousands of Closed Circuit Television (CCTV) and from billions of mobile video phones we actually cannot realize the existent volume of videos. A video program can be divided into scenes, and a scene may be composed of one or more frames. A scene usually communicates to some consistent event in a video program, such as a sequence of frames making up a dialogue scene in comedy movies, or a fighting scene in action videos [2]. Consequently, the videos retrieval with content-based instead of text-based, plays a very important role in multimedia system. For comprehensive reviews of previous CBVR techniques, please see [2~7]. Most previous CBVR systems allow automatic retrieval based on characteristics and distribution of color, shape, and texture. We can categorize CBVR Systems into two types according to the technique they utilize to extract features: *1. Global features based category,* global features such as different types of histograms are obtained from the entire image. Different global features similarity measures are used in the literature varying from simple methods like gray level histogram [8] or average intensity measure [9] to pair-wise comparison [10], and color histograms [11]. However most of the global based methods fail in the presence of severe motion or illumination changes. Furthermore, frames with totally different spatial layout can have similar global measure which is a common shortcoming for these techniques. For more information, please see [12~19]. *2. Region based category,* the image is divided into segments and then features are extracted from each segment. Region based approaches try to overcome the disadvantage of the global features based methods by considering the spatial distribution of the objects in the frame. These schemes include region based likelihood measure [20] and region based color histogram [21]. The local changes caused by camcorder and object movement can considerably alter the content are the common drawbacks of region based approaches. Motion compensation approaches [22] try to overcome this disadvantage by eliminating the motion difference between regions before comparing them. For more information, please see [23~30]. Each category contains many challenges. Although color plays an important role in the most systems for CBVR systems, the potential of color is not yet completely tapped. A problem of color arises if the illumination or color saturation is different between the query frames and the test frames. Most previous CBVR systems cannot consider different size, the defocus and noise problems, various lighting condition, partial occlusion, and diverse color saturation at the same time.

In the investigation, we present a CBVR system that can handle different size, miscellaneous color saturation, blurred and noise conditions, dissimilar illumination circumstances, partial occlusion, and contemplating of spatial relation at the same time. Furthermore, our new approach can keep both benefits of the global features based category and the region based category. The overview of our system is shown in Fig. 2. The designed system contains three phases. First, we resize all frames of videos to decrease the effects of variation in size, and expedite the speed. Second, we convert each frame of videos to a color cipher. Finally, we compare the color ciphers, e.g., cipher1 and cipher2 (cipher1 is color cipher of the query frame and cipher2 is color cipher of the frame in the database). Subsequently, return the matching weight. Afterward we compare cipher1 and cipher3 (cipher3 is color cipher of another frame in the database), and return the matching weight, and so on. The rest of the paper is organized as follows. In section 2, color cipher coding and color ciphers comparison are illustrated. Experimental results are displayed in section 3. Finally, conclusions are given in section 4.

II. Color Cipher Coding and Ciphers Comparison

The leading principle for our approach is simplicity and speed. First, we resize all frames of videos to reduce the effects of variation in size, and accelerate the speed. Since the videos are allowed to have different sizes, all frames of videos are normalized to a standard size (i.e. 20 × 20 pixels) in this step. Herein, all frames of videos are resized by the bicubic interpolation technique as described in Gonzalez et al. [31].

A. Color Cipher Coding

Since RGB color space is a 3-dimensional vector space, and each pixel, p (i), is defined by an ordered triple of red, green, and blue coordinates, (r (i), g (i), b (i)), which represent the intensities of red, green, and blue light color respectively. We realize that the values of r, g, and b are totally different with altered illumination conditions. However, the relative values between r (i), g (i), and b (i) are very similar. Therefore, we utilize 8 rules to transfer each frame of videos to a color cipher as below:

If a pixel 235 =< r (i) =< 255, 235 =< g (i) =< 255, and 235 =< b (i) =< 255 , then assigns the pixel as 'W'; (white color)

If a pixel 0 =< r (i) =< 20, 0 =< g (i) =< 20, and 0 =< b (i) =< 20, then assigns the pixel as 'K'; (black color)

If a pixel r (i) > g (i) >= b (i), then assigns the pixel as 'R'; (the first series of "Red" colors)

If a pixel r (i) >= b (i)> g (i), then assigns the pixel as 'S'; (the second series of "Red" colors)

If a pixel g (i) > r (i) >= b (i), then assigns the pixel as ' G'; (the first series of "Green" colors)

If a pixel g (i) >= b (i) > r (i), then assigns the pixel as 'H'; (the second series of "Green" colors)

If a pixel b (i) > r (i) >= g (i) , then assigns the pixel as 'B'; (the first series of "Blue" colors)

If a pixel b (i) >= g (i) > r (i), then assigns the pixel as 'C'; (the second series of "Blue" colors)

An example demonstrates the 20 X 20 pixels 32 bits color map with white and black, and its color cipher [We use purple color (e.g., W) instead of white color to able to be seen by readers.] is shown as Fig. 3. We can observe the "R" and "S" present two series of red colors, the "G" and "H" show the two series of green colors, the "B" and "C" demonstrate two series of blue colors, the "W" represents the white color, and "K" displays the black color respectively.

An instance illustrates how to obtain a 2D color cipher is shown as Fig. 4. Fig. 4 (a) An original frame of sport videos (352X 240 pixels); (b) Resized frame of sport videos (20 X 20 pixels); (c) Resized the 20 X 20 pixels frame of sport videos to 322 X 322 pixels) to be seen clearly by readers; (d) Transfer the frame of the resized frame of sport videos (20 X 20 pixels) to a 2D color cipher array. From the 2D cipher array, you can see the layout of the sportsman with a gesture of victory (V). You can see the reflection of spatial relation. Since the 8 rules as above, we can obtain the impression of the characters "G" and "H" present two series of green colors. For instance, we can see the green grass in the frame of videos that is transferred to "G" (the first series of "Green" colors) and the light brown earth in the frame of videos that is transferred to "R" (the first series of "Red" colors) as demonstrated as Fig. 4. Subsequently, each frame of videos will become a 2D cipher array, and then we will convert the 2D cipher array to a 1D cipher as below:

KKKCCCGGGCCCHCBCCCCC…RRHHHRRWWWWRRR (20 X 20 = 400 characters)

We can realize the power of discrimination between different frames of videos because 400 characters present 8^{400} (= 2^{1200}) permutations. The 2^{1200} permutations should have enough ability to distinguish most videos.

B. Color Cipher Comparison

We compare each element of cipher1 to the same location element in cipher2 (cipher1 is color cipher of the query frame and cipher2 is color cipher of the frame in the database), where cipher1 and cipher2 are equal-size cipher of characters. Subsequently, return the matching weight. Next, we compare each element of cipher1 to the same location element in cipher3 (cipher3 is color cipher of another frame in the database), and return the matching weight, and so on. When the same location character is the same one (e.g. both are ″R″), we increase 1 to the matching weight, and else we increase 0. For instance, if two frames of videos have all the same characters, then the maximum matching weight should be 400. If the matching weight is 400, then the distance is 0. The more similar frames of videos should have higher matching weight and the lower distance.

III. Experimental Results

The experimental database contains 31,566 MLB sports frames. The MLB sports frames are taken from TV video programs. The original/normal extracting the frames of videos is 30 frames per second (fps), but these extracting frames are too similar. Therefore, we extract the MLB sports frames with 3 frames per second (fps). Since it is very arduous to find enough similar frames with noise, blur, partial occlusion, disparate brightness, dissimilar color saturation, and different sizes, we add these conditions to the frames (e.g. LP means "enhance brightness to the frames", LM means "diminish intensity to the frames", CSP denotes "increase color saturation to the frames", CSM symbolizes "decrease color saturation to the frames", RS signifies "reduce the sizes of the frames", OC designates "partial occlusion the frames", and BN indicates "make indistinct first, then add noise to the frames", and NB represents "insert noise first, next blur the frames" using Photoshop 7.0.1). Therefore, in our database, we collect MLB sports frames with noise, blur, partial occlusion, different sizes, dissimilar illumination conditions, and diverse color saturations.

Besides, we compare our new system with R. P. Kumar's system [12]. The R. P. Kumar's system proposed a methodology based on regression line features for further reducing the computational complexity of these multiresolution histogram based techniques. The detail on performance evaluation of multiresolution histograms and wavelet based multiresolution histogram can be found in [12, 13 and 14].

The first example is shown as Fig. 5. Fig. 5(a) demonstrates the R. P. Kumar's system is not work for different lighting circumstances. Fig. 5(b) exhibits ours is perfect in various illumination conditions. The second illustration is displayed as Fig. 6. Fig. 6 (a) illustrates the R. P. Kumar's system is not spotless for partial moving object conditions (only some parts are moving). Fig. 6(b) exhibits ours is wonderful for partial moving object conditions. The third exhibition is demonstrated as Fig.7. Fig. 7 (a) displays the R. P. Kumar's system is not faultless for different color saturation situations. Fig. 7(b) illustrates ours is ideal for various color saturation circumstances. The fourth exposition is demonstrated as Fig. 8. Fig. 8(a) demonstrates the R. P. Kumar's system is deficient in blurred circumstances. Fig. 8(b) illustrates ours is outstanding in blurred situations. The fifth show is demonstrated as Fig. 9. Fig. 9(a) presents the R. P. Kumar's system is not work in "blurred first, then add noise" circumstances. Fig. 9(b) illustrates ours is marvelous in "blurred first, then add noise" conditions. The sixth presentation is displayed as Fig. 10. Fig. 10(a) demonstrates the R. P. Kumar's system is deficient in "add noise first, next blurred the frames" circumstances. Fig. 10(b) illustrates ours is outstanding in "add noise first, next blurred the frames" conditions. The seventh demonstration is exhibited as Fig. 11. Fig. 11(a) exhibits the R. P. Kumar's system is inadequate in occlusion circumstances. Fig. 11(b) illustrates ours is marvelous in occlusion situations

From the above examples, their system has 57 faults from 63 retrieval results. On the other hand, ours has 0 faults from 63 retrieval results. Therefore, we can profess our new system is superior to R. P. Kumar's system because their system cannot handle above conditions. Our new system not only can handle different size, miscellaneous color saturation, blurred and noise conditions, dissimilar illumination circumstances, and partial occlusion, but also consider the layout/spatial relation of the color. Consequently, our retrieval system is more reliable.

IV. Conclusion

One of the main differences between a content based videos retrieval system and a text based videos retrieval system is the capability of the previous one can rank videos by the degree of similarity with the query frame of MLB sports frames, namely, similarity-based retrieval. Conversely, a text based videos retrieval system typically process queries based on precise match. Most established and common platforms of videos frames retrieval utilize some processes of adding metadata such as captioning, keywords, or descriptions to the MLB sports frames. Afterward retrieval can be performed over the annotation words. Manual videos frames annotation is time-consuming, laborious and expensive. The text-based retrieval methods could be retrieved if the videos frames are well-annotated. In other words, the data without annotation make them incapable of being retrieved. Since we transfer each frame of videos frames to a color cipher, the videos frames retrieval system becomes an analogous text based videos retrieval system. Since each character/letter of a cipher contains a series of colors (e.g., red, green, blue, white, or black), our system can conquer different size, assorted brightness conditions, miscellaneous color saturation, partial occlusion, blurred and noise states, and tolerates some dissimilarity between the result and the query frames of videos frames at the same time. Unlike most region-based retrieval systems, no segmentation of images is needed in our approach. Moreover, the ciphers comparison is very fast in computer; accordingly, our approach is very speedy. In other words, our system keeps both advantages of the content based videos retrieval system (similarity-based retrieval) and a text based videos retrieval system (very rapid and mature). Furthermore, our new approach can keep both benefits of the global features based category and the region based category. We make video frames searching more ordinary, comfortable, and straightforward. In the future, we hope video frames searching will become more widespread as the way we currently search text information on the World Wide Web.

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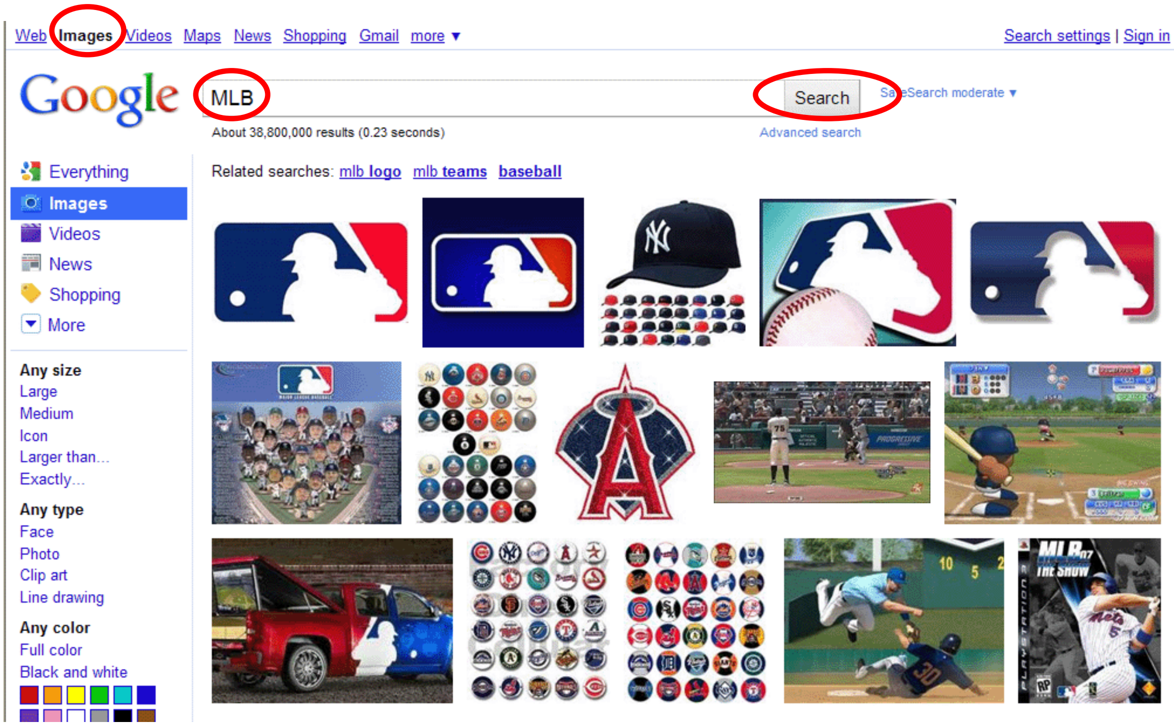

Fig. 1 Searching by keywords (e.g., MLB) on the World Wide Web in Google

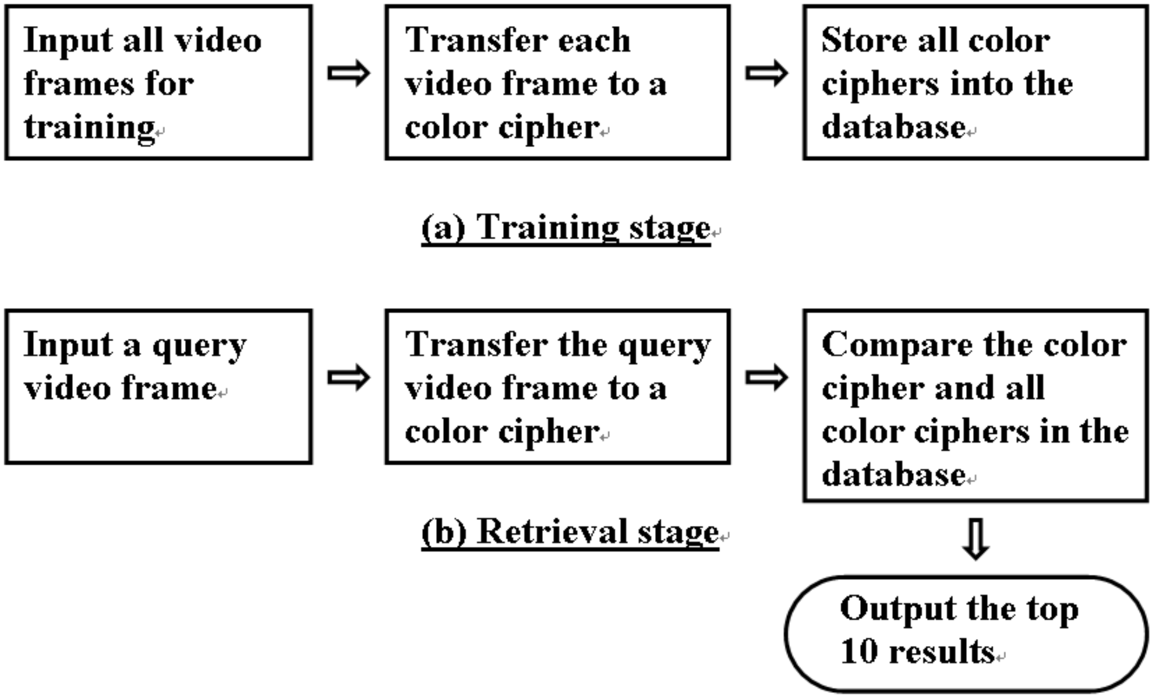

Fig. 2 Overview of our system

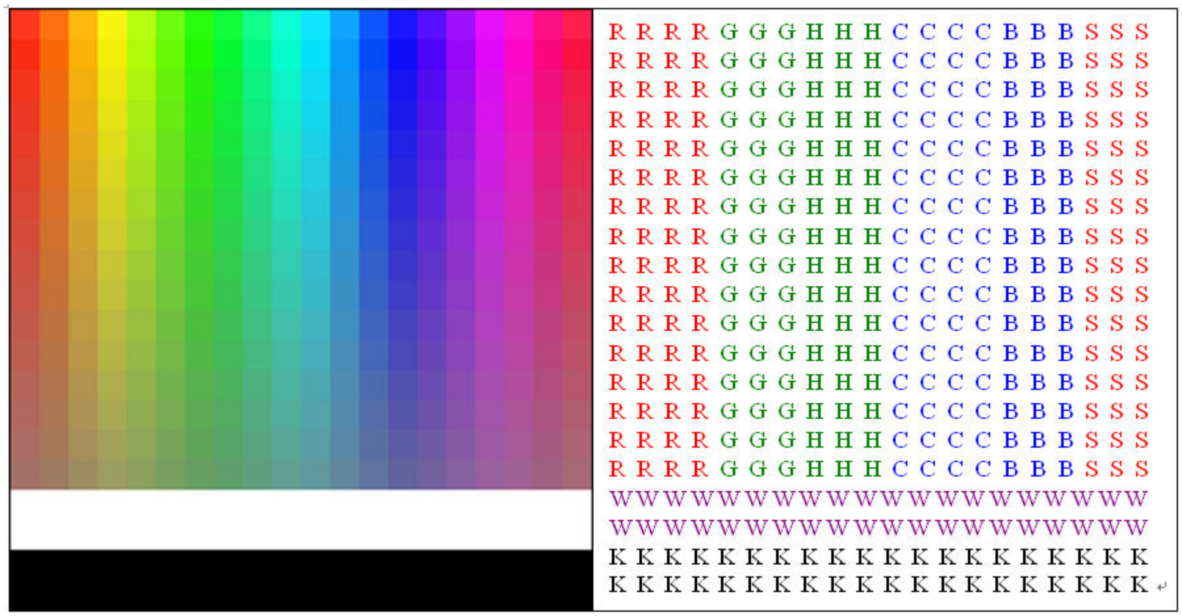

Fig. 3 the 20 X 20 pixels 32 bits color map with white and black, and its color cipher [We use purple color (e.g., W) instead of white color to be seen clearly by readers.]

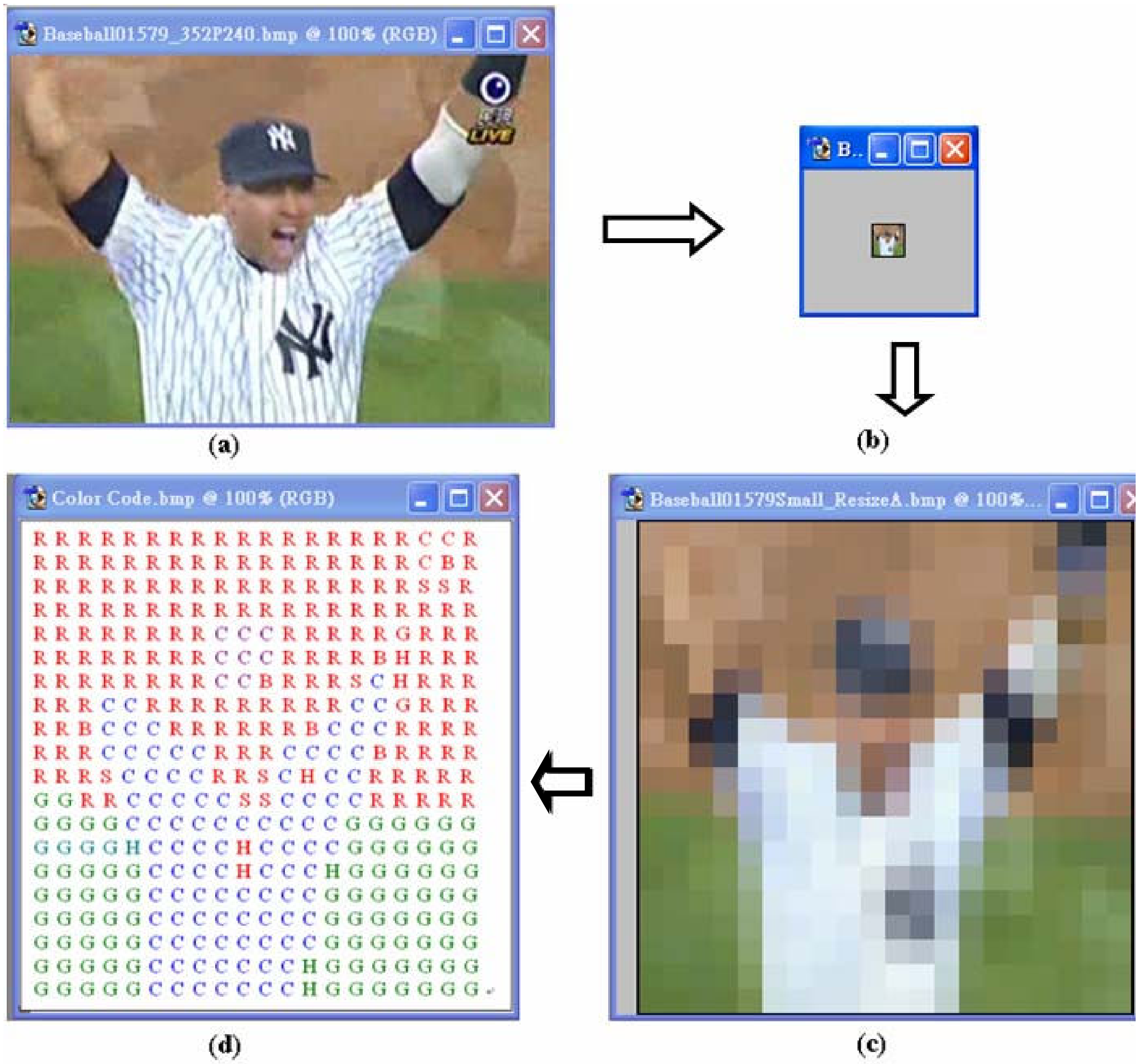

Fig. 4 (a) An original frame of sport videos; (b) Resized frame of sport videos (20 X 20 pixels) ; (c) Resized the 20X20 pixels frame of sport videos to 322 X 322 pixels) to be seen clearly by readers; (d) Transfer the frame of the resized frame of sport videos (20 X 20 pixels) to a color cipher array. From the 1D cipher array, you can see the layout of the sportsman with a gesture of victory.

Fig. 5(a) demonstrates the R. P. Kumar's system is defective in various lighting circumstances. The error detection is maked with red circles.

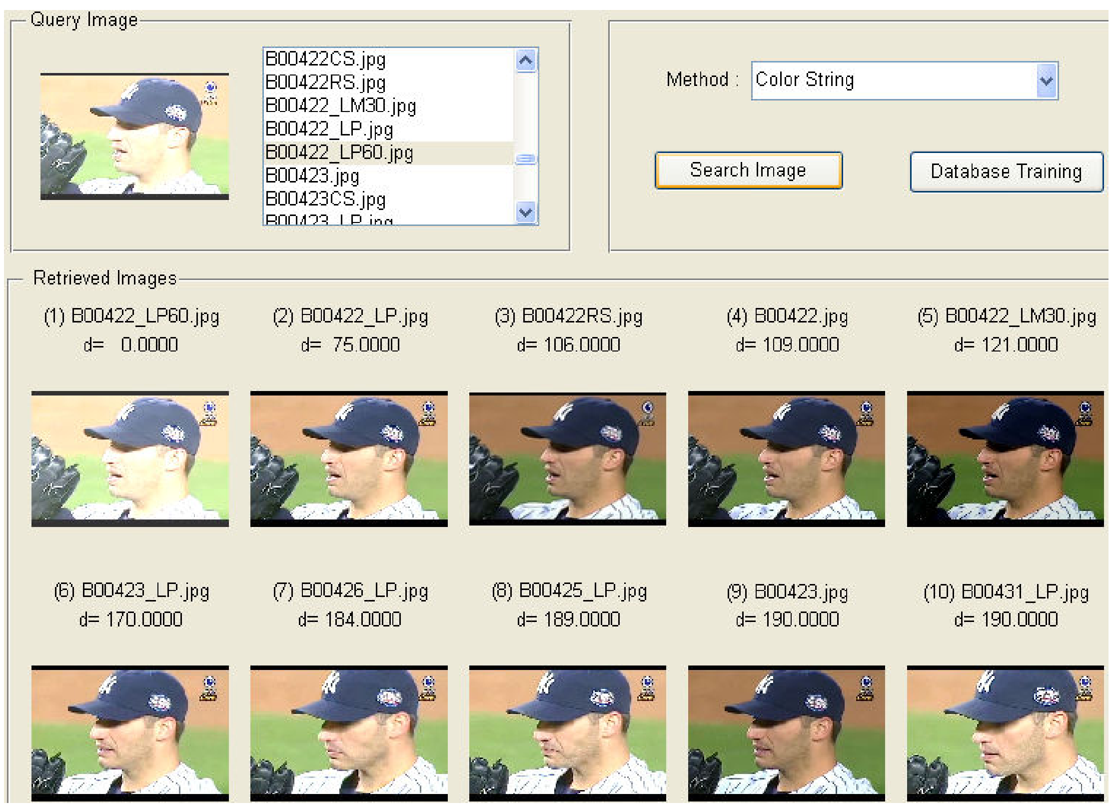

Fig. 5(b) exhibits ours is perfect in various lighting conditions.

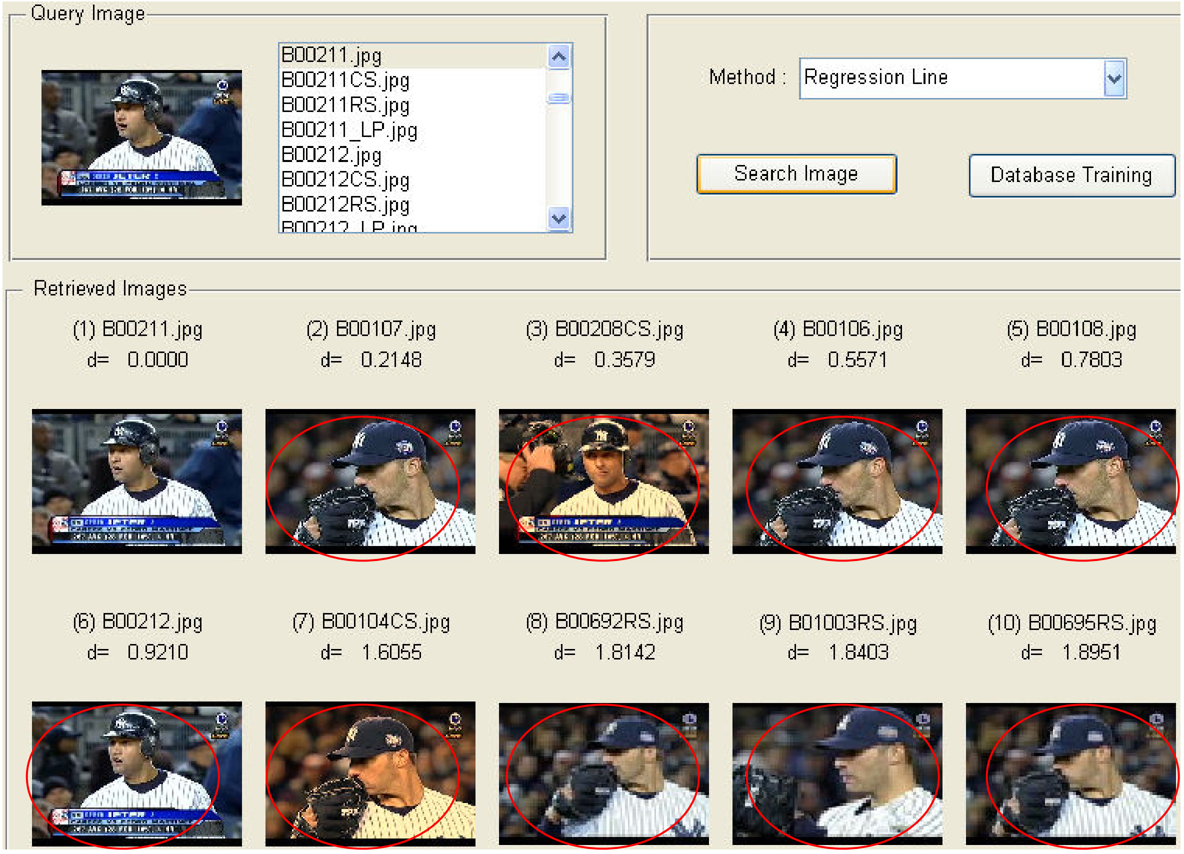

Fig. 6 (a) displays the R. P. Kumar's system is not spotless for contemplating of spatial relation (only some parts are moving). The error detection is marked with red circles.

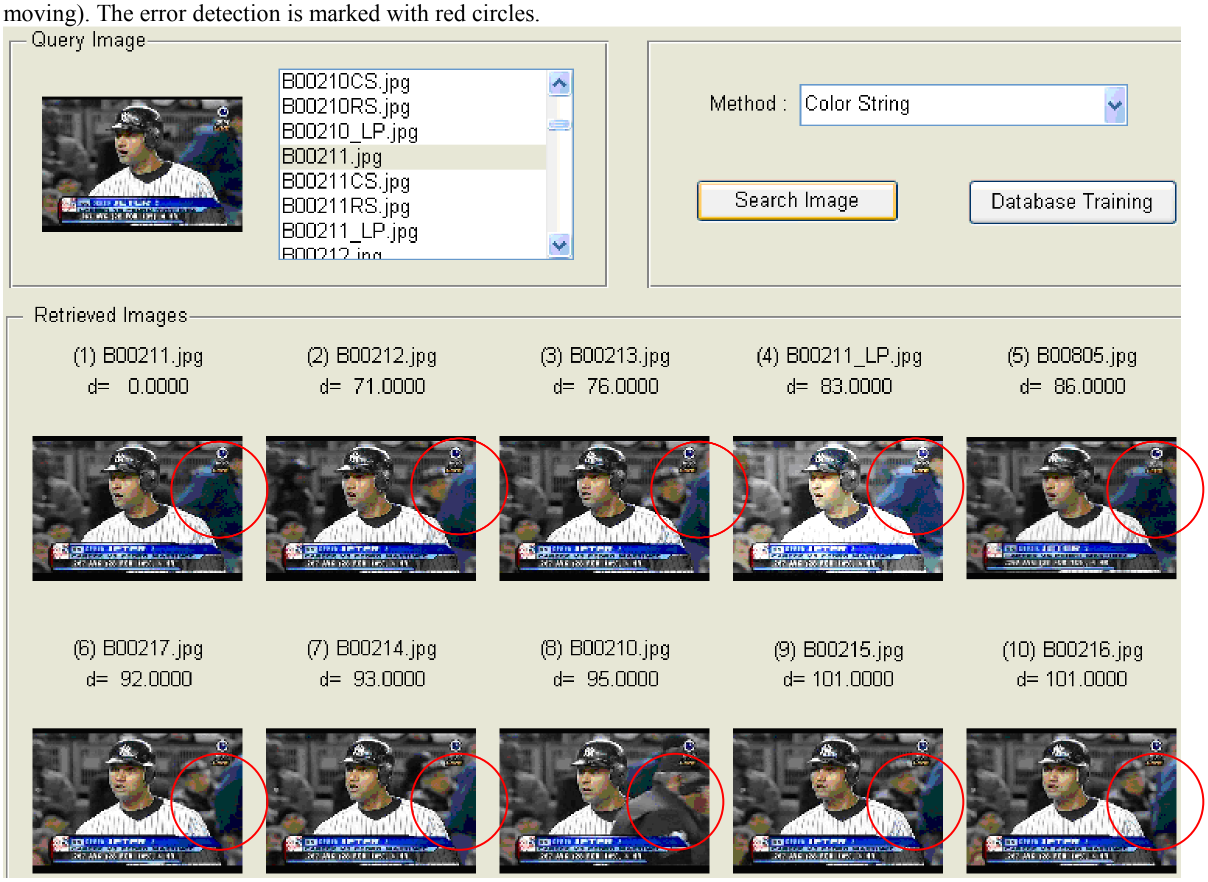

Fig. 6(b) illustrates ours is wonderful for contemplating of spatial relation (Only some parts are moving, and the moving parts are marked with red circles.)

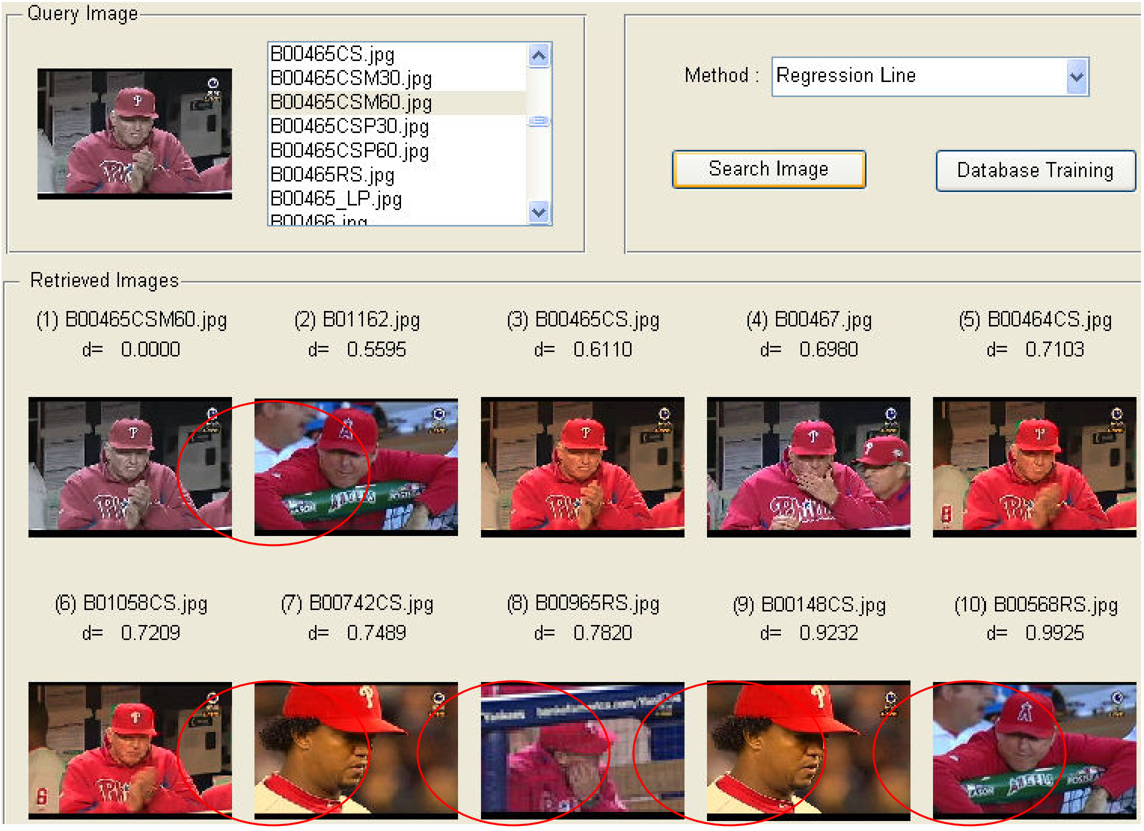

Fig. 7(a) demonstrates the R. P. Kumar's system is defective in diverse color saturation situations.

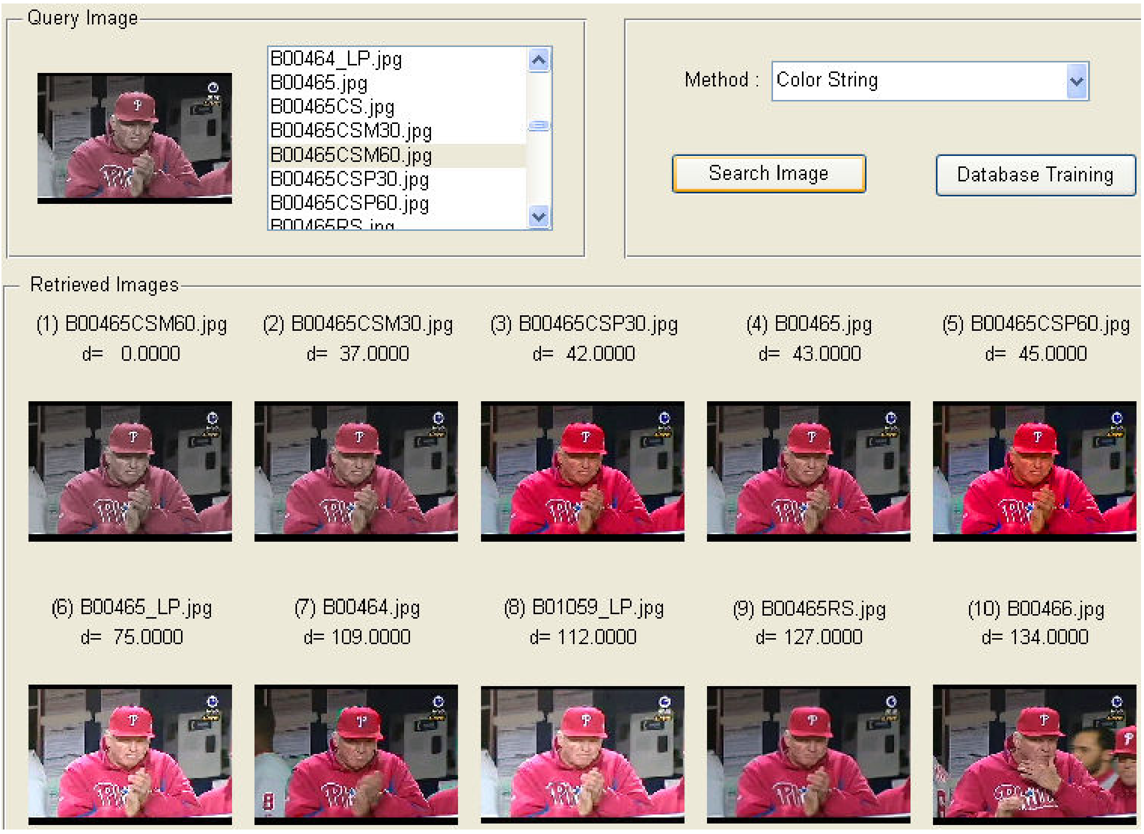

Fig. 7(b) illustrates ours is remarkable in sundry color saturation conditions.

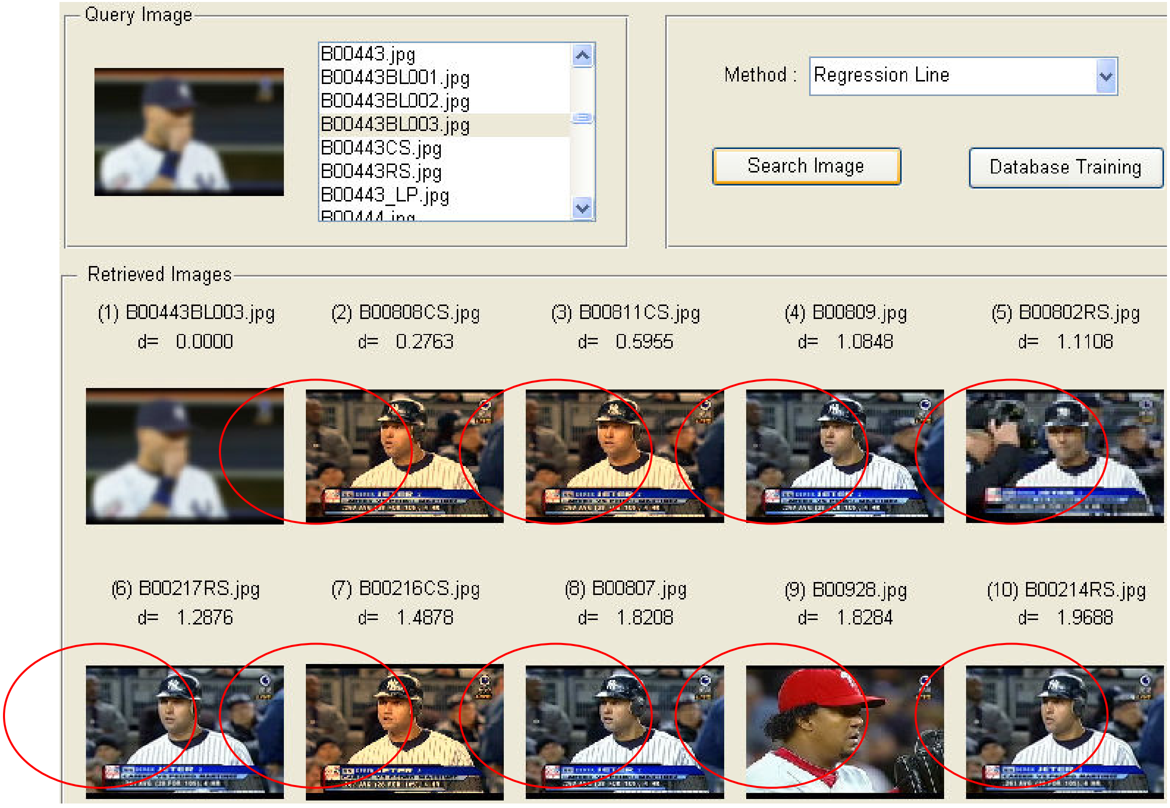

Fig. 8(a) demonstrates the R. P. Kumar’s system is imperfect in blurred circumstances.

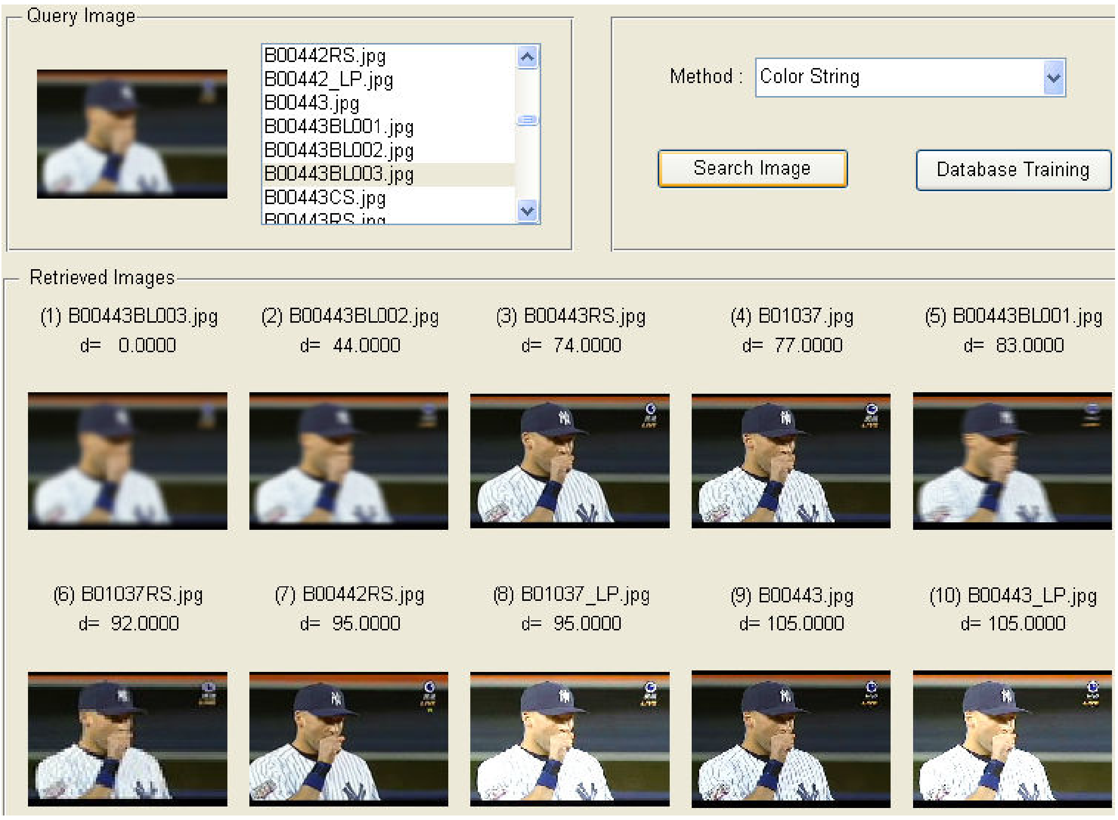

Fig. 8(b) illustrates ours is outstanding in blurred situations.

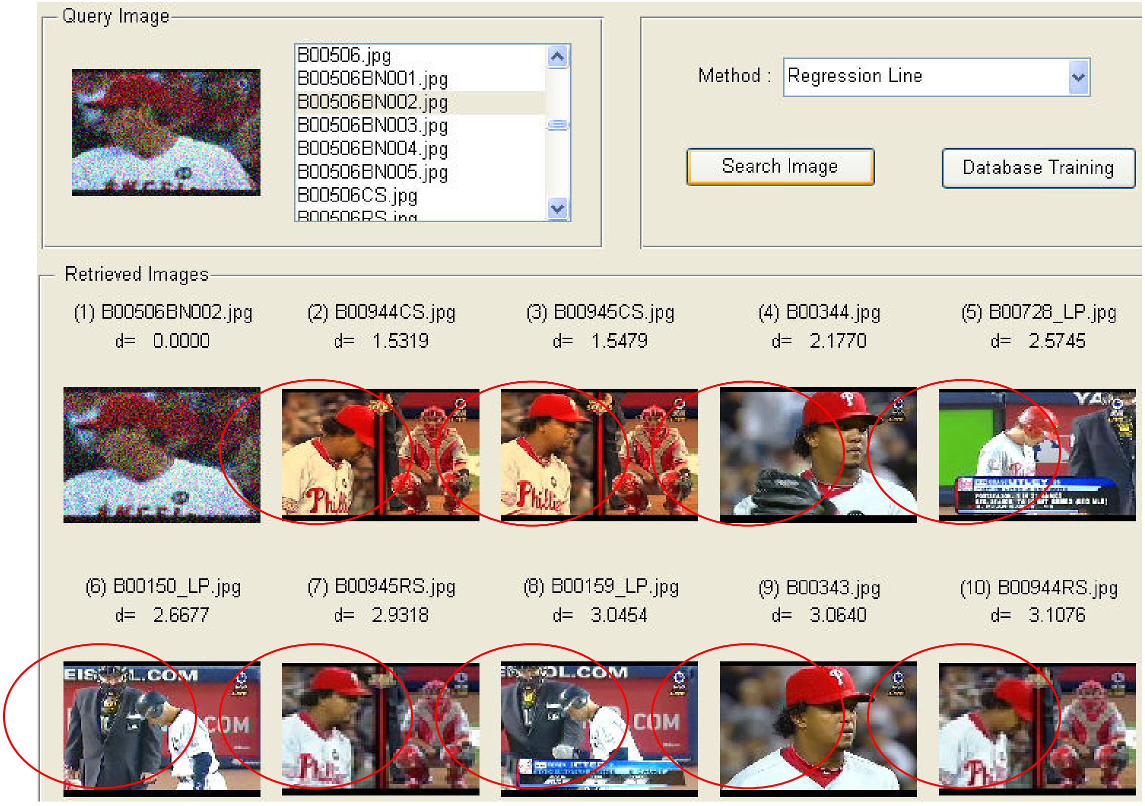

Fig. 10(a) demonstrates the R. P. Kumar’s system is not work in "blurred first, then add noise" circumstances.

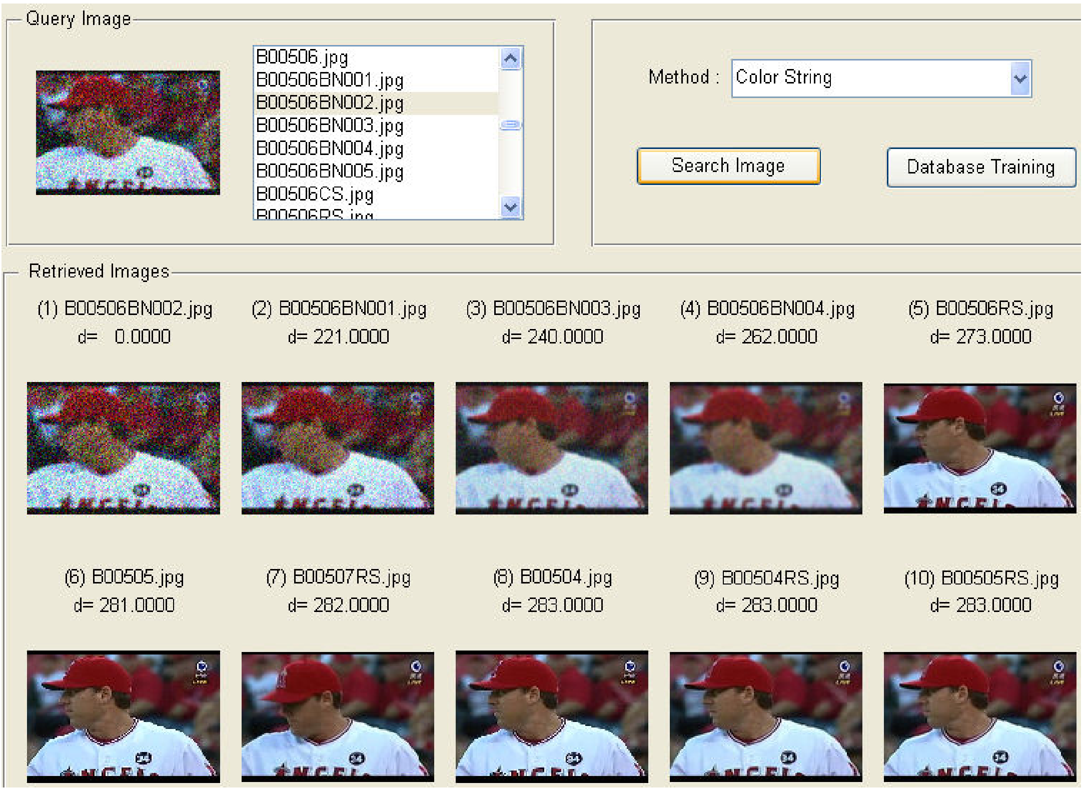

Fig. 10(b) illustrates ours is marvelous in "blurred first, then add noise" conditions.

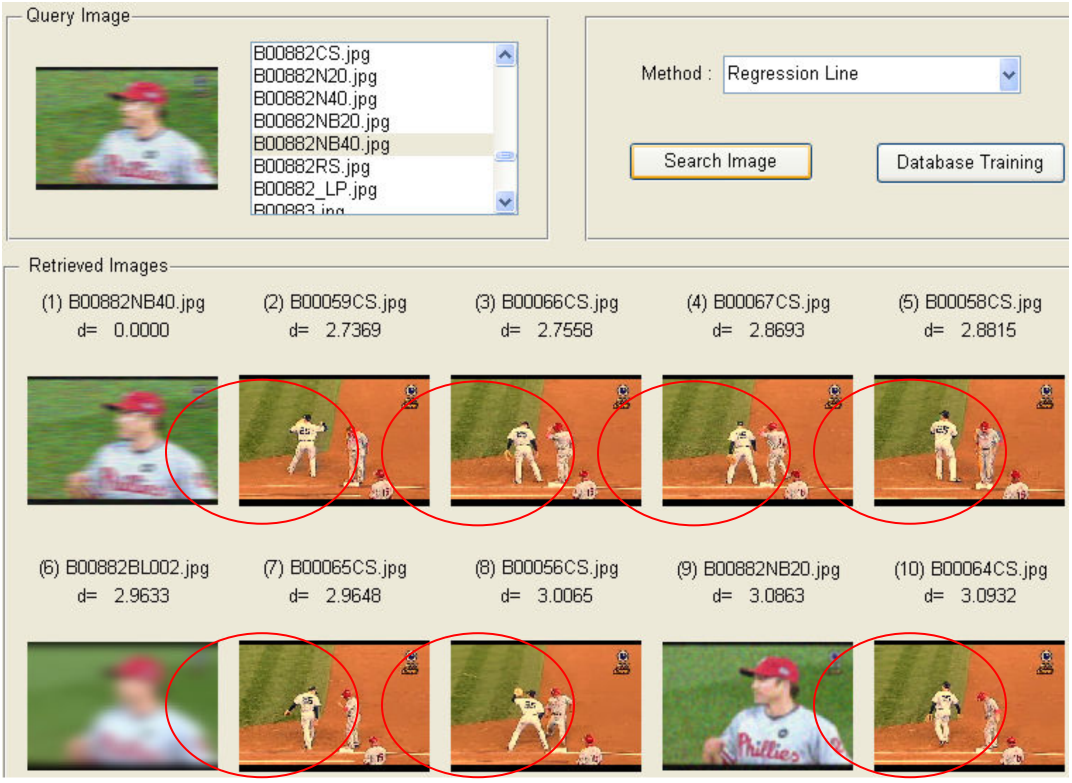

Fig. 10(a) demonstrates the R. P. Kumar's system is deficient in "add noise first, next blurred the frames" circumstances.

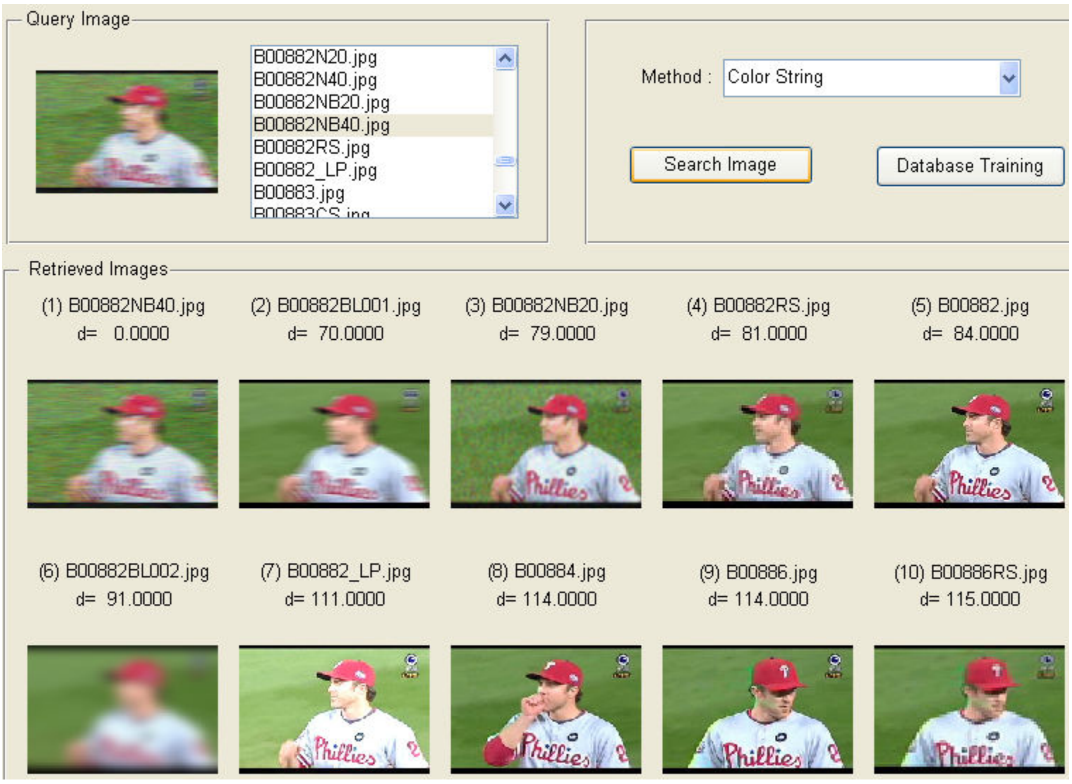

Fig. 10(b) illustrates ours is outstanding in "add noise first, next blurred the frames" conditions.

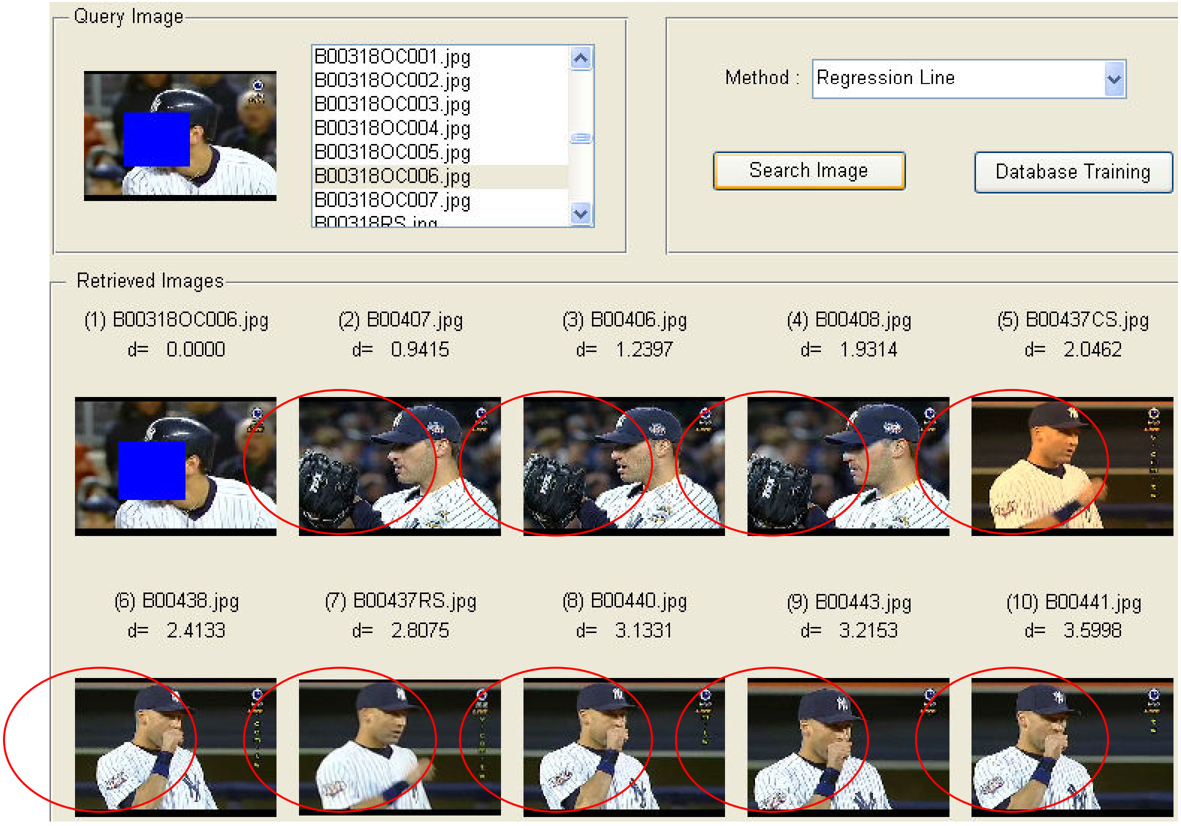

Fig. 11(a) demonstrates the R. P. Kumar's system is unsatisfactory in occlusion circumstances.

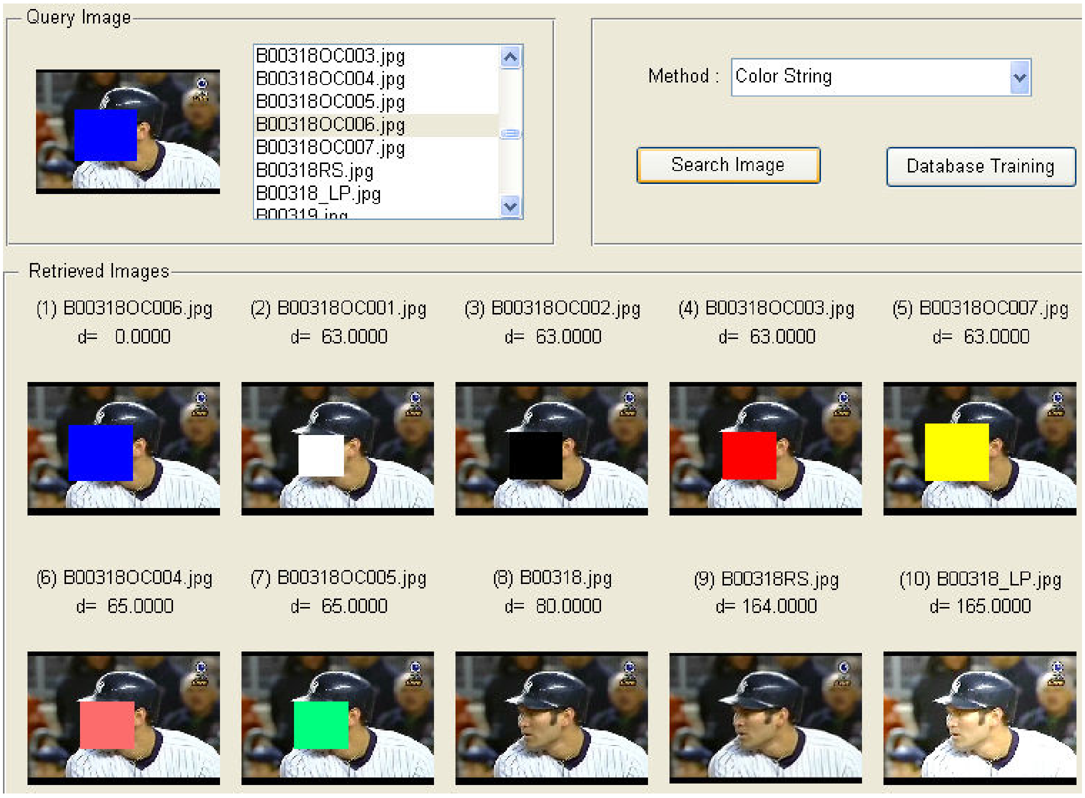

Fig. 11(b) illustrates ours is remarkable in occlusion situations.