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Robust and discriminative zero-watermark scheme based on invariant features and similarity-based retrieval to protect large-scale DIBR 3D videos

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Abstract: Digital rights management (DRM) of depth-image-based rendering (DIBR) 3D video is an emerging area of research. Existing schemes for DIBR 3D video cause video distortions, are vulnerable to severe signal and geometric attacks, cannot protect 2D frames and depth maps independently, or have difficulty handling large-scale videos. To address these issues, a novel zero-watermark scheme based on invariant features and similarity-based retrieval to protect DIBR 3D video (RZW-SR) is proposed in this study. In RZW-SR, invariant features are extracted to generate master and ownership shares to provide distortion-free, robust and discriminative copyright identification under various attacks. Different from conventional zero-watermark schemes, our proposed scheme stores features and ownership shares correlatively and designs a similarity-based retrieval phase to provide effective solutions for large-scale videos. In addition, flexible mechanisms based on attention-based fusion are designed to protect 2D frames and depth maps, either independently or simultaneously. The experimental results demonstrate that RZW-SR has superior DRM performance compared to existing schemes. First, RZW-SR can obtain the ownership shares relevant to a particular 3D video precisely and reliably for effective copyright identification of large-scale videos. Second, RZW-SR ensures lossless, precise, reliable and flexible copyright identification for 2D frames and depth maps of 3D videos.

Keywords: DIBR 3D video; zero-watermark scheme; invariant feature; similarity-based retrieval; attention-based fusion; copyright identification

1. Introduction

Protecting the copyrights of three-dimensional (3D) videos has become a crucial issue [4, 26, 33, 45]. On the one hand, the risk of copyright infringement for 3D videos has increased because 3D videos, which can provide better immersive experiences to viewers than traditional 2D videos, have become more and more popular over the Internet [22, 32, 40, 46]. On the other hand, the illegal copying and distribution of 3D videos will cause more serious losses to their owners than that of 2D videos because the production costs of 3D videos are much higher.

In this study, DIBR 3D video is chosen as the protection target for the following two reasons. First, 3D videos stored in DIBR format can reduce storage and transmission-bandwidth requirements compared with stereoscopic format [31, 40]. Second, DIBR is a key technique for converting existing 2D videos to 3D videos, and 3D videos synthesized using DIBR have much lower costs than those using stereo videos because they do not require different cameras to capture video frames from various viewpoints.

Compared with the protection of traditional 2D videos, the protection of DIBR 3D videos is more complex. Original 2D frames with depth maps in 3D videos can be converted into synthesized frames. Therefore, the watermark should be obtained from either the original 2D frames, synthesized frames or depth map. Because synthesized frames after DIBR conversion are different from original 2D frames and their pixels are shifted horizontally compared to the original, the protection scheme for 3D videos should be DIBR invariant. In addition, producers of 2D frames and depth maps are possibly different if 3D videos are synthesized from existing 2D videos. In this situation, copyrights of 2D frames and depth maps should be protected independently. Otherwise, they should be protected simultaneously.

Watermarking is one of the most popular methodologies for handling digital rights management (DRM) issues [4, 25, 39, 44]. The existing watermark schemes for DRM of DIBR-based 3D videos, which can mainly be classified into 2D frame-based watermark, depth map-based watermark and zero-watermark schemes, still have room for improvement: 1) 2D frame-based watermark schemes [1-3, 6-7, 9, 13, 20, 23, 26, 31, 34, 36, 47], which only embed watermarks into 2D frames, introduce irreversible distortions to the video content [33]. In addition, they ignore the situation in which the producers of 2D frames and depth maps may be different and thus cannot protect the copyright of depth maps independently. 2) For the depth map-based watermark schemes [8, 28-29, 33, 37-38, 42], which only embed watermark into depth maps, their robustness against severe signal attacks and geometrical attacks is insufficient [30]. In addition, they cannot protect the copyright of 2D frames independently. Finally, they cannot extract any copyright information from the 3D videos transmitted and stored by two synthesized frames. 3) Zero-watermark

schemes [30, 45] generate ownership shares, which indicate the mapping relationships between video features and the watermark, without any direct watermark embedding. Zero-watermark schemes are more promising than the other two classes of watermarking schemes because they are distortion-free and robust against many types of severe attacks. However, zero-watermark schemes are based on the premise that the precise ownership share relevant to a video has already been obtained for effective copyright identification. Otherwise, the copyright of this video cannot be identified correctly, and the verification of an illegal copy would fail. This still needs improvement because it is difficult for zero-watermark to obtain the precise ownership share when processing large-scale 3D videos due to the lack of an efficient indexing mechanism. Fortunately, it is noted that the methods based on manifold similarity and retrieval [14-16,49] have the potential to address this problem.

To overcome the abovementioned disadvantages, we propose a novel zero-watermark scheme for copyright protection of DIBR 3D video (RZW-SR) by fusing the similarity-based retrieval into the architecture of conventional zero-watermark in this study. In our proposed scheme, features of 2D frames and depth maps are first extracted by calculating the centroids of normalized variations between temporally informative representative images (TIRI) [11] and video frames. These TIRI-variation-centroid-based (TIRIVC) features are sufficiently robust and discriminative. Then, the master shares and ownership shares are generated based on these features and the watermark information according to the visual secret sharing (VSS) method [35]. The extracted features and their relevant ownership shares are stored, and the injective index relationships between them are established. For a queried 3D video, the similarity-based retrieval phase is first executed, in which its features are extracted and compared with the stored features, which is not performed in the conventional zero-watermark schemes. If any match occurs, the master shares are then generated from the extracted features. Finally, the copyright ownership of an illegal 3D video is identified by stacking the generated master shares with the ownership shares obtained according to the retrieval results. For both similarity-based retrieval and copyright identification, flexible mechanisms are designed. When the copyrights of 2D frames and depth maps are different, they are retrieved separately, and their copyrights are identified independently. Otherwise, the retrieval and copyright identification results are fused based on an attention-based fusion method [18] to enhance the DRM performance.

The key contributions of our proposed scheme are as follows:

- 1) To the best of our knowledge, it is the first scheme to fuse similarity-based retrieval with a zero-watermark technique to protect large-scale DIBR 3D videos.
- 2) TIRIVC features are designed to ensure the distinguishability of different 3D videos and robustness

against various signal, geometrical and DIBR attacks for effective similarity-based retrieval and copyright identification.

- 3) Flexible mechanisms using attention-based fusion are designed for both similarity-based retrieval and copyright identification to better satisfy the requirements for protecting DIBR 3D videos.
- 4) Comprehensive comparisons are made to demonstrate the superiority of our proposed scheme compared with the state-of-the-art watermark schemes for protecting DIBR 3D videos.

Fig. 1 summarizes how the proposed RZW-SR differs from existing 2D frame-based watermark, depth map-based watermark and zero-watermark schemes for protecting 3D DIBR videos. On the one hand, compared with existing 2D frame-based and depth map-based watermark schemes, copyrights of both 2D frames and depth maps are identified either independently or simultaneously without any video distortion in RZW-SR. On the other hand, compared with the existing zero-watermark schemes, ownership shares relevant to a particular 3D video can be obtained precisely and reliably based on the similarity-based retrieval when processing large-scale videos in RZW-SR. The coloured parts of Fig. 1 emphasize these differences. Specifically, the red-coloured parts show the disadvantages of existing 2D frame-based watermark, depth map-based watermark and zero-watermark schemes, whereas the blue-coloured parts demonstrate the superiority of our proposed RZW-SR.

The rest of the paper is organized as follows. In Section II, the related works are listed. In Section III, the proposed RZW-SR is described in detail. The experimental results and analyses are presented in Section IV, and the conclusions are drawn in Section V.

2. Related work

Existing schemes for copyright protection of DIBR-based 3D video can be mainly classified into three categories, which are 2D frame-based watermark schemes, depth map-based watermark schemes and zero-watermark schemes. Each category is individually described below.

Fig. 1. Structural differences in watermark schemes: (a) 2D frame-based watermark; (b) depth map-based watermark; (c) zero-watermark; and (d) our proposed RZW-SR

2.1 2D frame-based watermark schemes

2D frame-based watermark schemes [1-3, 6-7, 9, 13, 20, 23, 26, 31, 34, 36, 47] utilize the characteristics of depth maps to achieve remarkable watermark robustness and imperceptibility. Lee et al. [26] proposed a scheme utilizing the areas with high motion on the z-axis and for the pixels to be hidden by rendering for watermark embedding to ensure watermark imperceptibility. Fan et al. [13] proposed a scheme in which depth-perceptual regions of interest (DP-ROI) are constructed for watermark embedding by integrating the foreground, the depth-edge and the grey-contour regions to achieve better watermark imperceptibility. For these schemes, the watermark can hardly be extracted from the synthesized frames because the pixels are shifted horizontally by DIBR, and thus the synchronism of watermark embedding and extraction is destroyed after the DIBR process. To address this issue, DIBR invariant schemes have been designed in some works. Kim et al. [20] proposed a scheme that quantizes the coefficients of a dual-tree complex wavelet transform (DT-CWT) to make use of the approximate shift invariance and directional selectivity of DT-CWT. Asikuzzaman et al. [2-3] also proposed DT-CWT based schemes in which the watermark is embedded in the chrominance channels of 2D frames to achieve stronger robustness. Lin et al. [31] proposed a robustness watermark scheme in which multiple watermarks are embedded, and the effects of watermark embedding order were studied. Niu et al. [7, 47] proposed histogram-shape-based schemes in which suitable groups of pixel histograms are selected for watermark embedding to enhance the watermark robustness against geometrical attacks and DIBR distortions. Al-Haj et al. [1] proposed a watermark scheme based on mathematical transforms in which the discrete wavelet transform (DWT) and the singular value decomposition (SVD) are utilized to provide complementary robustness against watermarking attacks. Chen et al. [9] proposed a scheme in which the watermark is embedded into contourlet subbands of the 2D frame to make use of the directional multiresolution image representation and convenient tree structures of the contourlet transform. Lee et al. [34] proposed a scheme in which embedding locations are selected based on a depth variation prediction map and watermarks are embedded in the 2D DWT domain by quantization index modulation (QIM). To further enhance the robustness against geometric attacks, several watermark schemes based on geometric resynchronization functions [6, 23, 36] have been proposed. In these schemes, the resynchronizations between watermarked and attacked video frames are achieved by embedding a pre-defined template [23] or utilizing local feature points [6, 36], such as scale-invariant feature transform (SIFT) descriptors.

2.2 Depth map-based watermark schemes

Depth map-based watermark schemes [8, 28-29, 33, 37-38, 42] restrict the modifications of depth maps below a certain threshold to keep the synthesized 3D videos undistorted. One category of depth map-based schemes is based on the unseen visible watermark (UVW) technique [10, 17]. Lin et al. [33] and Pei et al. [37-38] proposed several schemes under this category. In these schemes, the synthesized 3D videos are undistorted under normal viewing conditions, and meaningful watermarks can be recognized when changing the rendering parameters. However, UVW-based watermarks are only viewable for subjective copyright identification and can hardly be extracted for objective copyright identification. In addition, the modifications of depth maps are restricted based on prior estimations, which limit the selection of watermark-embedding methods and thus weaken the watermark robustness. To address these two issues, Liu et al. [29] proposed an advanced unseen extractable watermark (AUEW) scheme. In this scheme, watermarks are embedded by quantizing the sum of AC coefficients in the pseudo 3D-DCT domain and can be directly extracted for objective copyright identification. Moreover, simulations of the embedding process rather than prior estimations are utilized to restrict the modifications of depth maps for stronger watermark robustness. The other category of depth map-based schemes is depth-no-synthesis-error-model-based reversible watermark schemes (D-NOSE-RW) [8, 28, 42]. In these schemes, watermarks are embedded into depth maps based on reversible watermark techniques, such as difference expansion [21], error prediction [43] and histogram modification [24], for lossless recovery of depth maps. Moreover, locations are selected based on the D-NOSE model for better 3D viewing experiences. Although the depth map-based watermark schemes can ensure the losslessness of the synthesized 3D videos, they are vulnerable to attacks and thus cannot provide reliable copyright identification when 3D videos are attacked.

2.3 Zero-watermark schemes

Zero-watermark schemes generate mapping relationships between video features and watermarks without direct watermark embedding to avoid content distortion. Liu et al. [30] proposed a robust zero-watermark scheme for DIBR 3D video (RZW_{DIBR}). In this scheme, the master shares are first generated by binarizing the 2D-DCT coefficients of temporally informative representative images (TIRI) [11] of 2D frames and depth maps. Then, the ownership shares are generated based on (2,2) VSS and stored for copyright identification instead of embedding watermarks into the video content. The copyrights of a queried 3D video are recovered by stacking the master shares and ownership shares. By utilizing the robust features of both 2D frames and depth maps, not only can the robustness of the zero-watermark scheme against various attacks be

ensured but also the copyrights of 2D frames and depth maps can be identified either independently or simultaneously to satisfy the different DRM requirements of DIBR 3D videos. However, the robustness of RZW_{DIBR} against geometrical attacks still needs improvements. Wang et al. [45] designed another robust zero-watermark scheme for stereo 3D video (RZW_{stereo}). In this scheme, features are extracted from the two stereo 2D frames based on ternary number theory and radial harmonic Fourier moments (TRRHFM). Although this scheme is robust against various signal attacks and geometrical attacks, it does not offer a protection solution for depth maps when it is used for DIBR 3D videos and thus cannot fully satisfy the DRM requirements when the copyrights of the 2D frames and depth maps are different. In addition, the distinguishability of TRRHFM-based features is not sufficient.

Although the existing zero-watermark schemes show more promising performances compared with 2D frame-based and depth map-based watermark schemes in terms of video quality or watermarking robustness, neither of them can obtain the precise ownership share effectively when processing large-scale 3D videos because no efficient indexing mechanism is designed in these zero-watermark schemes. In addition, neither of the existing zero-watermark schemes can guarantee sufficient robustness against geometrical attacks and distinguishability for different 3D videos at the same time. Our proposed RZW-SR scheme fuses the similarity-based retrieval with zero-watermark techniques to handle large-scale 3D videos. In addition, RZW-SR designs novel robust and discriminative features with flexible retrieval and copyright identification mechanisms to ensure flexible, reliable and precise copyright identification at the same time. Our proposed RZW-SR is explained in detail in the following section.

3. Proposed scheme

The proposed scheme includes three phases, which are the copyright-registration phase, similarity-based retrieval phase, and copyright-identification phase, as shown in Fig. 2. Each phase is individually described below.

Fig. 2. Procedure of our proposed scheme

3.1 Copyright-registration phase

In the copyright-registration phase, feature and ownership-share databases of both 2D frames and depth maps are constructed from their features and watermark information, as shown in Fig. 3.

Fig. 3. Copyright-registration phase of our proposed scheme

3.1.1 Feature extraction

In our study, the same feature-extraction methods of 2D frames and depth maps are designed. The procedures of feature extraction are shown in Fig. 4 and listed below.

Fig. 4. Feature extraction of our proposed scheme

Step 1. Normalize both the 2D frames and depth maps, from $w \times h \times l$ to $320 \times 320 \times 100$ based on spatial and temporal resampling and smoothing. Here, w and h are the width and height of the original video frames, respectively. l is the frame number of the processed 3D video clip. Select the luminance of the normalized 2D frames and depth maps, denoted as R_{2d} and R_{depth} , for feature extraction. In this manner, the robustness of extracted features against resizing and temporal attacks can be enhanced.

Step 2. Subsample and average R_{2d} and R_{depth} in the temporal domain to construct their TIRIs, denoted

as $TIRI_{2d}$ and $TIRI_{depth}$, respectively, in (1).

$$TIRI_c(i, j) = \sum_{m=1}^M R_c(i, j, k) \times w_k / \sum_{m=1}^M w_k; \quad (1)$$

$$w_k = a^k, \quad k = 5 \times m.$$

where $c \in (2d, depth)$, $TIRI_{2d}(i, j)$ and $TIRI_{depth}(i, j)$ are the pixels in the i th row and j th column of the TIRIs of 2D frames and depth maps, respectively. $R_{2d}(i, j, k)$ and $R_{depth}(i, j, k)$ are the pixels in the i th row and j th column of the k th frame of normalized 2D frames and depth maps, w_k is the weight associated with $R_{2d}(i, j, k)$ and $R_{depth}(i, j, k)$, $1 \leq i \leq 320$, $1 \leq j \leq 320$, $1 \leq m \leq 20$, $M=20$, and a is between 0 and 1. When a is close to 1, the generated TIRI is more similar to an averaged image and contains more temporal information. Therefore, the feature generated from the TIRI is more robust. Otherwise, the generated TIRI contains more spatial information but less temporal information, and thus the feature generated from the TIRI is more discriminative. In our study, a is selected to be 1. In this manner, the generated TIRI contains more temporal information, and thus the feature robustness is stronger against noise addition and temporal attacks.

Step 3. Generate TIRI-based variations $D_{2d}(i, j, k)$ and $D_{depth}(i, j, k)$ by calculating the maximal absolute differences between the central pixels in normalized frames and the 8 spatial neighbourhood pixels in the TIRIs, as shown in (2).

$$D_c(i, j, k) = \max(|TIRI_c(i \pm 1, j \pm 1) - R_c(i, j, k)|); \quad (2)$$

where $c \in (2d, depth)$, $2 \leq i \leq 319$, $2 \leq j \leq 319$ and $1 \leq k \leq 100$.

When a video frame suffers geometrical attacks, such as rotation or flipping, the 8 spatial neighbourhoods of each pixel are still located around the central pixel. Only their relative positions are modified, which does not greatly affect the maximal absolute differences calculated in (2). Therefore, the utilization of 8 spatial-neighbourhood pixels enhances the robustness against rotation and flipping attacks.

The neighbourhood pixels in TIRIs rather than those in the normalized frames are utilized to exploit temporal properties and relationships of video frames. In this manner, the feature robustness against noise addition and temporal attacks is enhanced. In contrast, the central pixels in the normalized video frames rather than those in TIRIs are utilized to exploit more detailed spatial properties of video sequences. In this manner, the feature distinguishability is enhanced.

Step 4. Normalize the TIRI-based variations, denoted as $N_{2d}(i, j, k)$ and $N_{depth}(i, j, k)$, using (3).

$$N_c(i, j, k) = \arctan(D_c(i, j, k) / TIRI_c(i, j)); \quad (3)$$

where $c \in (2d, depth)$. In this manner, the feature is more robust when against global attacks such as contrast modification, brightness modification and gamma transform.

Step 5. Partition the frames consisting of normalized TIRI-based variations into a central circle and $N-1$

concentric rings. The radius of the central circle and the widths of concentric rings are set to r .

For each pixel (i, j, k) in the k_{th} frame, its distance $Dist(i, j, k)$ to the centre point of this frame (i_o, j_o, k) is first calculated as shown in (4).

$$Dist(i, j, k) = \sqrt{(i - i_o)^2 + (j - j_o)^2} \quad (4)$$

Then, partition n of pixel (x, y, k) is calculated based on $Dist(i, j, k)$, as shown in (5).

$$n = \lfloor Dist(i, j, k) / r \rfloor \quad (5)$$

In our study, the size of frames consisting of normalized TIRI-based variations is 320×320 , N equals 16, and r equals 10. When the videos are rotated or flipped, the pixels partitioned in this manner still belong to their original associated circle or ring partitions. Therefore, feature robustness against rotation and flipping attacks is ensured. In addition, the regions outside the largest ring are not utilized in our study due to the following two reasons. On the one hand, the main visual of a video frame is usually concentrated in its central region. Therefore, features generated by discarding the regions outside the largest ring do not lose much important visual information. On the other hand, because these regions are the most common places for logo insertion and edge cropping attacks, the feature robustness against these attacks can be enhanced by discarding the regions outside the largest ring.

Step 6. Take the pixel values in TIRIs as the weights of normalized TIRI-based variations. Calculate the centroids of normalized TIRI-based variations in each partition using (6) and generate the intermediate features of 2D frames and depth maps, denoted as f_{2d} and f_{depth} , using (7).

$$v_c(n, k) = \frac{\sum_{(n-1)r \leq Dist(i, j, k) \leq nr} TIRI_c(i, j) N_c(i, j, k)}{\sum_{(n-1)r \leq Dist(i, j, k) \leq nr} TIRI_c(i, j)}; \quad (6)$$

$$f_c = [v_c(1, 1) \dots v_c(N, 1) \dots v_c(1, K) \dots v_c(N, K)]; \quad (7)$$

where $c \in (2d, depth)$ and K is the number of frames consisting of normalized TIRI-based variations. In our study, K equals 100, and the dimensionality of f_{2d} and f_{depth} is $K \times N$ and equals 1600.

Step 7. Normalize the intermediate features by their mean and standard deviation as shown in (8) to generate the final features, fn_{2d} and fn_{depth} . Store fn_{2d} and fn_{depth} in the 2D frame and depth map feature databases, respectively, for similarity-based retrieval and copyright identification. Here, $c \in (2d, depth)$.

$$\begin{aligned}
\mu_c &= \frac{1}{NK} \sum_{i=1}^{NK} f_c(i); \\
\sigma_c &= \sqrt{\frac{1}{NK-1} \sum_{i=1}^{NK} (f_c(i) - \mu_c)^2}; \\
fn_c(i) &= \frac{f_c(i) - \mu_c}{\sigma_c};
\end{aligned} \tag{8}$$

3.1.2 Generation of master shares and ownership shares

(m, n) VSS (where $m \leq n$) was proposed by Naor *et al.* [35]. In VSS, one binary image is split into n shares and can be recovered from l shares when $l \geq m$. Otherwise, the image cannot be recovered. $(2, 2)$ VSS is a typical VSS, in which each pixel of a binary image is substituted by a pair of shares consisting of four sub-pixels. A white pixel is split into two identical shares, whereas a black pixel is split into two complementary shares.

$(2-2)$ VSS is a low-cost injective function and utilized in our RZW-SR to generate the master shares and ownership shares. In this manner, mapping relationships between features and copyright information is injective. Therefore, robustness and distinguishability of features can be maintained during the procedures of generating master shares and ownership shares. The detailed procedures of generating master shares and ownership shares are listed below.

Step 1. Binarize the features of 2D frames and depth maps by their median values to construct intermediate vectors, as shown in (9).

$$\begin{aligned}
I_c(i) &= 1, \text{ if } fn_c(i) > t_c; \\
I_c(i) &= 0, \text{ if } fn_c(i) \leq t_c
\end{aligned} \tag{9}$$

where $c \in (2d, depth)$, $1 \leq i \leq K \times N$, t_{2d} is the median value of f_{2d} , and t_{depth} is the median value of f_{depth} .

Step 2. Rearrange the intermediate vectors I_{2d} and I_{depth} to construct intermediate matrices V_{2d} and V_{depth} , which are of size 40×40 . Generate the master shares of 2D frames and depth maps, which are denoted as M_{2d} and M_{depth} , according to the $(2, 2)$ VSS as shown in (10).

$$m_c(i, j) = \begin{cases} \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, & V_c(i, j) = 1; \\ \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, & V_c(i, j) = 0; \end{cases} \tag{10}$$

where $c \in (2d, depth)$; $m_{2d}(i, j)$ and $m_{depth}(i, j)$ are non-overlapping 2×2 blocks of M_{2d} and M_{depth} ; $1 \leq i \leq 40$ and $1 \leq j \leq 40$.

Step 3. Generate ownership shares of 2D frames and depth maps, which are denoted as O_{2d} and O_{depth} ,

according to the (2, 2) VSS as shown in (11).

$$o_c(i, j) = \begin{cases} \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, W_c(i, j) = 1; \\ \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, W_c(i, j) = 0; \\ \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, W_c(i, j) = 1; \\ \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, W_c(i, j) = 0; \end{cases} \quad (11)$$

where $c \in (2d, depth)$; $o_{2d}(i, j)$ and $o_{depth}(i, j)$ are non-overlapping 2×2 blocks of O_{2d} and O_{depth} ; $W_{2d}(i, j)$ and $W_{depth}(i, j)$ are the watermark bits of the 2D frame and depth map; $1 \leq i \leq 40$ and $1 \leq j \leq 40$.

Step 4. Store the generated O_{2d} and O_{depth} in ownership databases and establish injective index relationships between these ownership shares and their relevant features, which have already been stored in feature databases, for copyright identification.

3.2 Similarity-based retrieval phase

When a 3D video is queried, a similarity-based retrieval phase is executed to find the stored features that match the features of the queried video, as shown in Fig. 5.

Fig. 5. Similarity-based retrieval phase of our proposed scheme

Features of queried 2D frames and depth maps, which are denoted as fn'_{2d} and fn'_{depth} , are first extracted following the same procedures in the copyright-registration phase. The normalized distances between queried features and original features in databases are measured using (12).

$$d_c = \frac{1}{L} \sum_{i=1}^L (fn_c(i) - fn'_c(i))^2 \quad (12)$$

where $c \in (2d, depth)$ and L is the length of the features. In our study, L equals $N \times K$. N is the number of partitions and equals 16, and K is the number of frames and equals 100.

To satisfy different DRM requirements of DIBR 3D videos, a flexible matching mechanism is designed in our study. In the case that the copyrights of 2D frames and depth maps are different, the features of 2D

frames and depth maps are retrieved separately and independently. Given the thresholds T_{2d} and T_{depth} , if any d_{2d} or d_{depth} is smaller than T_{2d} or T_{depth} , respectively, the 2D frames or depth maps of two DIBR 3D videos are considered to be near-duplicates and the queried DIBR 3D video is considered to be an illegal copy. Otherwise, normalized feature distances of 2D frames and depth maps are fused. It will be better if the function F_D satisfies the heterogeneity and monotonicity for distance fusion [18]. The heterogeneity is defined in (13), and the monotonicity is defined in (14).

$$F_D(d_1, d_2) > F_D(d_1 - \varepsilon, d_2 + \varepsilon) \quad (13)$$

$$\begin{aligned} F_D(d_1, d_2) &< F_D(d_1 + \varepsilon, d_2); \\ F_D(d_1, d_2) &< F_D(d_1, d_2 + \varepsilon). \end{aligned} \quad (14)$$

where $0 < \varepsilon \leq d_1 \leq d_2$; d_1 and d_2 are distance values to be fused.

To strictly satisfy the heterogeneity and monotonicity simultaneously, an attention-based fusion function for distances is designed inspired by the method of [18] as below.

$$\begin{aligned} x_1 &= \frac{1}{d_{2d}} + \frac{1}{d_{depth}}; \\ x_2 &= \left| \frac{1}{d_{2d}} - \frac{1}{d_{depth}} \right| \\ F_D(d_{2d}, d_{depth}) &= \frac{1}{\frac{1}{2}(x_1 + \frac{1}{1+\gamma}x_2)}. \end{aligned} \quad (15)$$

where γ is a constant and is empirically set to 0.1 in our study.

Given a threshold T_{fusion} , the two DIBR 3D videos are considered to be near-duplicates and the queried DIBR 3D video is considered to be an illegal copy if any distance value fused in (15) is smaller than T_{fusion} .

Because 2D frames have more texture information than depth maps, whereas the distribution of pixel values in the depth maps is regional, the feature robustness characteristics of 2D frames and depth maps are complementary to a certain extent. Therefore, the distance fused in (15) further enhances the reliability of similarity-based retrieval against different attacks.

If the queried DIBR 3D video is considered to be an illegal copy, a copyright-identification phase is implemented. Otherwise, the procedures of RZW-SR are finished.

3.3 Copyright-identification phase

In this phase, ownership shares, which are relevant to the matched features, are stacked with the master shares of illegal DIBR 3D videos to recover the copyright information. The detailed procedures are shown in Fig. 6 and described below.

Fig. 6. Copyright-identification phase of our proposed scheme

3.3.1 Recovery of copyright information

Step 1. Obtain the ownership shares relevant to the matched features from ownership databases.

Step 2. Generate the master shares of illegal DIBR 3D videos, M'_{2d} and M'_{depth} , from f'_{2d} and f'_{depth} , respectively, following the same procedure as in the copyright-registration phase.

Step 3. Stack the generated master shares with the obtained ownership shares to construct intermediate copyright-identification matrices S_{2d} and S_{depth} , as shown in (16).

$$s_c(i, j) = \begin{cases} \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, o_c(i, j) = \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}; \\ \begin{bmatrix} 0, 0 \\ 0, 0 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}, o_c(i, j) = \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}; \\ \begin{bmatrix} 0, 0 \\ 0, 0 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, o_c(i, j) = \begin{bmatrix} 1, 0 \\ 0, 1 \end{bmatrix}; \\ \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, & \text{if } m_c(i, j) = \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}, o_c(i, j) = \begin{bmatrix} 0, 1 \\ 1, 0 \end{bmatrix}; \end{cases} \quad (16)$$

where $c \in (2d, depth)$; $s_{2d}(i, j)$ and $s_{depth}(i, j)$ are non-overlapping 2×2 blocks of S_{2d} and S_{depth} ; $1 \leq i \leq 40$ and $1 \leq j \leq 40$.

Step 4. Recover the watermark information of the 2D frame and depth map W'_{2d} and W'_{depth} , from S_{2d} and S_{depth} , respectively, using (17).

$$W'_c(i, j) = \begin{cases} 1, & \sum s_c(i, j) \geq 2; \\ 0, & \sum s_c(i, j) < 2; \end{cases} \quad (17)$$

where $c \in (2d, depth)$; $1 \leq i \leq 40$, $1 \leq j \leq 40$, $1 \leq x \leq 2$, and $1 \leq y \leq 2$.

3.3.2 Identification of copyright ownership

To satisfy the different DRM requirements of DIBR 3D videos, a flexible copyright-identification mechanism is designed in our study.

In the case that the copyrights of the 2D frames and depth maps are different, they are identified separately and independently by calculating their own bit error rates (*BERs*) between the original watermark and the recovered watermark as shown in (18).

$$BER_c = \frac{\sum W_c(i, j) \oplus W'_c(i, j)}{i \times j}; \quad (18)$$

where $c \in (2d, depth)$, $1 \leq i \leq 40$ and $1 \leq j \leq 40$.

Otherwise, the *BERs* of 2D frames and depth maps are fused. It will be better if the function F_{BER} satisfies the heterogeneity and monotonicity for *BER* fusion, which is similar to the distance fusion. Therefore, a similar attention-based fusion function for *BERs* is also designed as below:

$$\begin{aligned} x_1 &= \frac{1}{BER_{2d}} + \frac{1}{BER_{depth}}; \\ x_2 &= \left| \frac{1}{BER_{2d}} - \frac{1}{BER_{depth}} \right| \\ F_{BER}(BER_{2d}, BER_{depth}) &= \frac{1}{\frac{1}{2}(x_1 + \frac{1}{1+\gamma}x_2)} \end{aligned} \quad (19)$$

where γ is a constant empirically set to 0.1 in our study.

The attention-based fusion further enhances the reliability of copyright identification because the complementary feature robustness of 2D frames and depth maps are analysed in the similarity-based retrieval phase.

4 Experimental Result and Discussion

4.1 Experimental Setup

In this study, the distinguishability and robustness of our designed feature are first evaluated in section 4.2. Then, the performances of similarity-based retrieval in our proposed RZW-SR are evaluated in section 4.3. In addition, performances of copyright identification in our proposed RZW-SR are assessed in section 4.4.

After that, the computational complexity of our proposed RZW-SR is tested and discussed in section 4.5. Finally, qualitative comparisons between our proposed RZW-SR and other schemes for DIBR 3D videos are presented in section 4.6.

Our testing database contains 200 different DIBR 3D video clips. Some of them are from the open datasets provided by the MPEG 3DAV group [12] and Interactive Visual Media Group of Microsoft Research [50]. Others consist of 2D frames selected from existing movies, with their depth maps manually calibrated by authors based on the method in [41]. The videos in [12] consist of 125 or 250 frames at 25 fps, and the videos in [50] consist of 100 frames at 15 fps. Their frame sizes are 720×576 and 1024×768 , respectively. For our manually generated DIBR video clips, they consist of 200 frames at 25 fps, and their frame sizes are 1920×1080 . A watermark image of size 40×40 is utilized for copyright identification. Four sequences of synthesized frames are generated by setting the baseline distances as 5% and 7% of the video frame width. These baseline distances have been chosen carefully because baseline distances larger than 7% may induce discomfort for 3D viewing [1, 40]. All original 2D frames, depth maps and synthesized frames suffer 14 types of attacks, with a total of 26 different attacks. As a result, a total of 32,000 sequences of queried videos, including 5,200 sequences of attacked 2D frames, 5,200 sequences of attacked depth maps, 800 sequences of original synthesized frames and 20,800 sequences of attacked synthesized frames, are generated to evaluate performances of the proposed RZW-SR. The types and parameters of the attacks are shown in Table 1. The 1st to 8th are signal attacks. The 9th to 12th are geometrical attacks. The last two are temporal attacks.

TABLE 1. Types of attacks

	Types	Parameters
Signal attacks	Gaussian blurring (GB)	window=9×9, variance=1; window=15×15, variance=1
	Average filtering (AF)	window=9×9; 15×15
	Median filtering (MF)	window=9×9; 15×15
	Changes in contrast (CC)	-30%; +30%
	Changes in brightness (CB)	-30%; +30%
	Gamma transform (GT)	$\gamma=0.6$; 1.4
	Gaussian noise addition (GN)	Mean=0, variance=0.005; Mean=0, variance=0.01
	Logo insertion in the upper-left (LI)	Logo size =32×32; 64×64
Geometrical attacks	Resizing (RS)	1/2 of original size; 1/5 of original size
	Crop from image edges (CR)	5%; 10%
	Rotation (RT)	45°; 90°
	Flip (FL)	Vertical, horizontal
Temporal attacks	Frame replacing randomly (FR)	Replacing rate=5%

4.2 Evaluation of feature distinguishability and robustness

In this section, we calculate the inter- and intra-feature distances to evaluate the feature distinguishability and robustness of the proposed RZW-SR, which indicate the accuracy and reliability of both similarity-based retrieval and copyright identification. The inter-feature distance means the feature distance between different video-clip pairs, whereas the intra-feature distance means the feature distance between the original and its attacked video. The mean inter- and intra-feature distances of our proposed RZW-SR are tested and compared with those of the other two zero-watermark schemes, which are RZW_{stereo} [45] and RZW_{DIBR} [30]. All of these distances are calculated in the same manner as shown in (12). Assuming that the features are totally independent, the theoretical value of the mean inter-feature distances of our proposed RZW-SR is 2, which has been proved in [19]. The theoretical values of the mean inter-feature distances of RZW_{stereo} [45] and RZW_{DIBR} [30] are both 0.5 because their features are both binarized. On the one hand, a feature is more discriminative if the mean inter-feature distance is closer to its theoretical value. On the other hand, a feature is more robust if the mean intra-feature distance is closer to 0. The results are listed in Table 2.

TABLE 2. Mean inter- and intra-feature distances of different schemes

		Mean inter-feature distances/theoretical values	Mean intra-feature distances
RZW_{stereo} [45]	2D frame	0.1436/0.5000	0.0311
	2D frame	0.4979/0.5000	0.1456
RZW_{DIBR} [30]	Depth map	0.4981/0.5000	0.2027
	Fuse together	0.4975/0.5000	0.1357
Our proposed RZW-SR	2D frame	1.9080/2.0000	0.0713
	Depth map	1.8519/2.0000	0.0917
	Fuse together	1.6990/2.0000	0.0337

As shown in Table 2, the mean inter-feature distances of our proposed RZW-SR and RZW_{DIBR} are close to their theoretical values, whereas the mean inter-feature distance of RZW_{stereo} is only 0.1436 and far from its theoretical value. Furthermore, the mean intra-feature distances of our proposed RZW-SR and RZW_{stereo} are close to 0 and are much smaller than those of RZW_{DIBR} . These results show that our designed features ensure sufficient distinguishability and robustness simultaneously and are superior to the features of RZW_{stereo} (not sufficiently discriminative) and RZW_{DIBR} (not sufficiently robust).

4.3 Evaluation of similarity-based retrieval performance

In this section, the false-negative rates P_{fn} with a fixed false-positive rate P_{fp} under all of these attacks are calculated to evaluate the retrieval performance of our proposed scheme. P_{fp} is the probability of classifying different videos as the same and indicates the retrieval accuracy, whereas P_{fn} is the probability of classifying the original and its attack videos as different and indicates the retrieval reliability. P_{fp} and P_{fn} are defined by (20)-(21). In our experiments, P_{fp} is fixed to a small value of 0.01. A retrieval function is more effective if P_{fn} is closer to 0. The results are listed in Tables 3 and 4.

TABLE 3. P_{fn} with $P_{fp} = 0.01$ under different attacks when utilizing original 2D frames, depth maps and their fusion

	Our proposed RZW-SR		
	2D frame	Depth map	Two together
GB 9×9	0.0000	0.0200	0.0000
GB 15×15	0.0000	0.0200	0.0000
AF 9×9	0.0100	0.0350	0.0000
AF 15×15	0.0100	0.0450	0.0000
MF 9×9	0.0100	0.0000	0.0000
MF15×15	0.0100	0.0000	0.0000
CC -30	0.0000	0.0000	0.0000
CC +30	0.0000	0.0150	0.0000
CB -30	0.0100	0.0000	0.0000
CB +30	0.0000	0.0400	0.0000
GT $\gamma=0.6$	0.0000	0.0000	0.0000
GT $\gamma=1.4$	0.0000	0.0000	0.0000
GN 0.005	0.0050	0.0650	0.0000
GN 0.01	0.0050	0.0900	0.0050
LI 32×32	0.0000	0.0000	0.0000
LI 64×64	0.0000	0.0400	0.0000
RS 1/2	0.0000	0.0000	0.0000
RS 1/5	0.0100	0.0050	0.0000
CR 5%	0.0000	0.1300	0.0100
CR 10%	0.0250	0.1450	0.0150
RT 45°	0.0050	0.1050	0.0000
RT 90°	0.0350	0.1450	0.0250
FL Vertical	0.0000	0.0000	0.0000
FL Horizontal	0.0000	0.0000	0.0000
FR 5%	0.0100	0.1450	0.0050
FD 5%	0.0350	0.0250	0.0150
Average value	0.0067	0.0412	0.0029

$$P_{fp} = \frac{N_{fp}}{N_{dis}} \quad (20)$$

$$P_{fn} = \frac{N_{fn}}{N_s} \quad (21)$$

where N_{fp} is the number of inter-feature distances smaller than a threshold, N_{dis} is the true number of different video clips, N_{fn} is the number of intra-feature distances larger than the threshold, and N_s is the true number of attacked videos.

Table 3 shows that all of the P_{fn} of our proposed RZW-SR when utilizing original 2D frames, utilizing depth maps and fusing them together are very small, with their maximal values as 0.0350, 0.1450, and 0.0250 and average values as 0.0067, 0.0412, and 0.0029. These results demonstrate that the similarity-based retrieval of our proposed RZW-SR is effective. In addition, P_{fn} obtained when fusing the two components together are even smaller than those obtained when only utilizing original 2D frames or depth maps, which demonstrates that the attention-based fusion enhances the performances of similarity-based retrieval when the copyrights of the original 2D frames and depth maps are the same. The reason for this phenomenon is that the feature robustness characteristics of 2D frames and depth maps are complementary because 2D frames have more texture information whereas depth maps are much smoother.

Table 4 shows that all of the P_{fn} of our proposed RZW-SR when only utilizing synthesized frames are still very small, with their maximal values as 0.0500, 0.0600, 0.0550, and 0.0750, respectively, and their average values as 0.0092, 0.0079, 0.0189, and 0.0114. For the synthesized frames without attacks, their P_{fn} are 0.0000, 0.0000, 0.0100 and 0.0000. In addition, P_{fn} obtained when fusing the synthesized frames and depth maps are just slightly larger than those when fusing the original 2D frames and depth maps, with their maximal values as 0.0300, 0.0400, 0.0350, and 0.0500 and average values as 0.0035, 0.0042, 0.0046, and 0.0052. These results demonstrate that the similarity-based retrievals of our proposed RZW-SR when utilizing (fusing) synthesized frames are still effective and that they are just slightly worse than when utilizing (fusing) original 2D frames. The reason for these results is that the features extracted from the original 2D frames and synthesized frames are similar. In addition, the P_{fn} obtained when fusing synthesized frames and depth maps are smaller than those when only utilizing synthesized frames or depth maps, which is consistent with the results listed in Table 3. These results demonstrate that the attention-based fusion also enhances the performances of similarity-based retrieval under DIBR distortions with various attacks.

Finally, we plot detection error trade-off (DET) graphs based on P_{fn} and P_{fp} in Fig. 7 to fully demonstrate the performances of similarity-based retrieval of the proposed RZW-SR.

Fig. 7 shows that all of the mean P_{fn} are less than 0.2 even when the P_{fp} is set to 10^{-4} . In addition, all of the DET graphs fusing the 2D frames (synthesized frames) and depth maps are below the graphs when only utilizing 2D frames (synthesized frames) or depth maps, respectively. These results demonstrate that both the accuracy and the reliability of the similarity-based retrieval in RZW-SR are sufficient. In addition, the performance of the similarity-based retrieval is even enhanced by designing the attention-based fusion when the copyrights of 2D frames and depth maps are the same.

TABLE 4. P_{fn} with $P_{fp} = 0.01$ under different attacks of our proposed RZW-SR when utilizing depth maps, synthesized frames, and their fusion

	Depth map	Baseline distance=5% frame width				Baseline distance=7% frame width			
		Synthesized	Two	Synthesized	Two	Synthesized	Two	Synthesized	Two
		frame (left)	together	frame (right)	together	frame (left)	together	frame (right)	together
Without attack	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
GB 9×9	0.0200	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
GB 15×15	0.0200	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
AF 9×9	0.0350	0.1500	0.0000	0.0100	0.0000	0.0200	0.0000	0.0150	0.0000
AF 15×15	0.0450	0.0200	0.0000	0.0100	0.0000	0.0250	0.0000	0.0150	0.0000
MF 9×9	0.0000	0.0100	0.0000	0.0100	0.0000	0.0200	0.0000	0.0150	0.0000
MF15×15	0.0000	0.0200	0.0000	0.0100	0.0000	0.0200	0.0000	0.0150	0.0000
CC -30	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
CC +30	0.0150	0.0050	0.0000	0.0000	0.0000	0.0150	0.0000	0.0000	0.0000
CB -30	0.0000	0.0100	0.0000	0.0050	0.0000	0.0200	0.0000	0.0050	0.0000
CB +30	0.0400	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
GT $\gamma=0.6$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
GT $\gamma=1.4$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
GN 0.005	0.0650	0.0050	0.0000	0.0000	0.0000	0.0150	0.0000	0.0000	0.0000
GN 0.01	0.0900	0.0100	0.0050	0.0050	0.0050	0.0200	0.0100	0.0050	0.0100
LI 32×32	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
LI 64×64	0.0400	0.0000	0.0000	0.0000	0.0000	0.0050	0.0000	0.0000	0.0000
RS 1/2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
RS 1/5	0.0050	0.0100	0.0000	0.0100	0.0000	0.0200	0.0000	0.0150	0.0000
CR 5%	0.1300	0.0050	0.0100	0.0150	0.0150	0.0250	0.0100	0.0150	0.0150
CR 10%	0.1450	0.0200	0.0150	0.0200	0.0150	0.0400	0.0150	0.0300	0.0150
RT 45	0.1050	0.0150	0.0100	0.0100	0.0150	0.0300	0.0150	0.0250	0.0200
RT 90	0.1450	0.0500	0.0300	0.0600	0.0400	0.0550	0.0350	0.0750	0.0500
FL Vertical	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0050	0.0000
FL Horizontal	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100	0.0000	0.0000	0.0000
FR 5%	0.1450	0.0200	0.0100	0.0100	0.0100	0.0300	0.0250	0.0150	0.1500
FD 5%	0.0250	0.0350	0.0150	0.0400	0.0150	0.0500	0.0150	0.0600	0.1500
Average value	0.0412	0.0092	0.0035	0.0079	0.0042	0.0189	0.0046	0.0114	0.0052

Fig. 7. DET graphs of the proposed RZW-SR when: (a) utilizing original 2D frames, utilizing depth maps and fusing them; (b) utilizing left synthesized frames (baseline=5%), utilizing depth maps and fusing them; (c) utilizing right synthesized frames (baseline=5%), utilizing depth maps and fusing them; (d) utilizing left synthesized frames (baseline=7%), utilizing depth maps and fusing them; and (e) utilizing right synthesized frames (baseline=7%), utilizing depth maps and fusing them.

Because injective index relationships between the features and ownership shares are established, the ownership share relevant to a particular DIBR 3D video can also be obtained precisely and reliably according to similarity-based retrieval results for the latter copyright identification phase.

4.4 Evaluation of copyright identification performance

The performance of copyright identification is mainly considered in terms of accuracy and reliability. For 2D frame and depth map-based watermark schemes, the copyright identification accuracy has been guaranteed because their watermarks are directly embedded into the 3D videos, and the possibility of extracting an accurate watermark from unwatermarked 3D videos is insignificant. For existing zero-watermark schemes, the copyright identification accuracy is not ensured because it is difficult for zero-watermark schemes to obtain the precise ownership share when processing large-scale 3D videos without an efficient indexing mechanism. For our proposed RZW-SR, the accuracy of copyright identification has been ensured in the similarity-based retrieval phase by setting P_{fp} to 0.01 because only the 3D video that has matching features would be used at the copyright identification phase. In this section, we mainly evaluate the reliability of

copyright identification by using our proposed RZW-SR. Specifically, we compare our proposed scheme with five distortion-free schemes for 3D videos in terms of watermarking robustness, which are UVW [38], D-NOSE-RW [42], AUEW [29], $\text{RZW}_{\text{stereo}}$ [45] and RZW_{DIBR} [30]. Note that lossy watermarking schemes are not included in this section for the fair comparison of watermarking robustness.

A subjective evaluation is first performed for the copyright identification comparison. The watermark images are recovered from both the 2D frames and the depth maps of a typical DIBR 3D video clip ‘Ballet’ in the open dataset [50] by using our proposed RZW-SR and compared with those detected by using UVW, D-NOSE-RW, AUEW and $\text{RZW}_{\text{stereo}}$. The results are shown in Table 5. RZW_{DIBR} is not included in the subjective evaluation because the copyright information in RZW_{DIBR} is features of watermark images rather than watermark images themselves, which can hardly be visually presented.

TABLE 5. Subjective evaluation of copyright-identification performances of different schemes

	UVW [38]	D-NOSE-RW [42]	AUEW [29]	$\text{RZW}_{\text{stereo}}$ [45]	Our proposed RZW-SR	
	(Depth map)	(Depth map)	(Depth map)	(2D frame)	2D frame	Depth map
Embedded watermark
Without attack
GB 9×9
GB 15×15
AF 9×9
AF 15×15
MF 9×9
MF15×15
CC -30
CC +30
CB -30
CB +30
GT $\gamma=0.6$

TABLE 5. Subjective evaluation of copyright-identification performances of different schemes (continued)

	UVW [38]	D-NOSE-RW [42]	AUEW [29]	RZW _{stereo} [45]	Our proposed RZW-SR	
	(Depth map)	(Depth map)	(Depth map)	(2D frame)	2D frame	Depth map
GT $\gamma=1.4$
GN 0.005
GN 0.01
LI 32×32
LI 64×64
RS 1/2
RS 1/5
CR 5%
CR 10%
RT 45°
RT 90°
FL Vertical
FL Horizontal
FR 5%
FD 5%

As shown in Table 5, watermarks recovered using our proposed RZW-SR are much clearer than those detected using UVW, D-NOSE-RW and AUEW under various attacks. The watermarks in UVW are only viewable but can hardly be extracted. Moreover, the watermarks detected by UVW can hardly be recognized under filtering, noise addition, severe resizing and rotation attacks. The watermarks extracted by D-NOSE-RW can hardly be recognized under filtering, contrast changing, brightness changing, noise addition, resizing, rotation and flipping attacks. The watermarks extracted by AUEW can hardly be recognized under severe filtering, heavy noise addition, rotation and flipping attacks. These results demonstrate that the copyright identification of our proposed RZW-SR is more reliable than those of UVW,

D-NOSE-RW and AUEW. Although the watermarks recovered by using RZW_{stereo} are also clear under all of the attacks, RZW_{stereo} does not protect the depth maps when the copyrights of the 2D frames and depth maps are different because its watermarks can only be recovered from the 2D frames. In contrast, our proposed RZW-SR can recover clear watermarks from both the 2D frames and depth maps and can protect these two components independently and reliably, which better satisfies the DRM requirements of DIBR 3D videos.

TABLE 6. Subjective evaluation of copyright-identification performance when utilizing synthesized frames

	Our proposed RZW-SR (baseline distance=5%)		Our proposed RZW-SR (baseline distance=7%)			Our proposed RZW-SR (baseline distance=5%)		Our proposed RZW-SR (baseline distance=7%)	
	Synthesized frame (left)	Synthesized frame (right)	Synthesized frame (left)	Synthesized frame (right)		Synthesized frame (left)	Synthesized frame (right)	Synthesized frame (left)	Synthesized frame (right)
Embedded watermark					Without attack				
GB 9×9					GB 15×15				
AF 9×9					AF 15×15				
MF 9×9					MF 15×15				
CC -30					CC +30				
CB -30					CB +30				
GT $\gamma=0.6$					GT $\gamma=1.4$				
GN 0.005					GN 0.01				
LI 32×32					LI 64×64				
RS 1/2					RS 1/5				
CR 5%					CR 10%				
RT 45°					RT 90°				
FL Vertical					FL Horizontal				
FR 5%					FD 5%				

In addition, the watermark images are also recovered from the synthesized frames of ‘Ballet’ by using our proposed RZW-SR. As shown in Table 6, the watermarks recovered from the synthesized frames using

our proposed scheme are still clear for copyright identification under all of the attacks, which demonstrates that our proposed RZW-SR can identify the copyrights of 2D frames reliably even when using the DIBR synthesized frames under various attacks.

To further evaluate the copyright-identification reliability of our proposed RZW-SR, objective evaluation is performed by calculating the mean *BERs* between the original watermark and watermarks recovered from attacked 3D videos. On the one hand, we calculate the mean *BERs* of our proposed RZW-SR when utilizing original 2D frames, utilizing depth maps, and fusing these two components together. The results are compared with those of D-NOSE-RW, AUEW, RZW_{stereo} , and RZW_{DIBR} as shown in Table 7. UVW is not included in the subjective evaluation because its watermarks are only viewable but can hardly be extracted for objective evaluation. On the other hand, we calculate the mean *BERs* of our proposed RZW-SR when utilizing synthesized frames and fusing them with their depth maps to evaluate our watermark robustness against DIBR distortions. The results are shown in Table 8.

Table 7 shows that the mean *BERs* of our proposed RZW-SR when utilizing original 2D frames, utilizing depth maps and fusing them together are very small. The results demonstrate that the copyright identification of our proposed RZW-SR is reliable under all of these attacks. In addition, the mean *BERs* when fusing 2D frames and depth maps together are even smaller than those when utilizing either of them alone. The results demonstrate that attention-based fusion enhances the copyright-identification performance. The reason for this phenomenon is the utilization of the complementary feature robustness of 2D frames and depth maps, as analysed in section 4.3.

Moreover, when the copyrights of 2D frames and depth maps are the same, our proposed RZW-SR and RZW_{DIBR} use these two components together. In this situation, the maximal *BER* of our proposed RZW-SR is 0.0870, which is still very close to 0. This value is much smaller than those of D-NOSE-RW, AUEW, and RZW_{DIBR} , which are 0.7259, 0.5873 and 0.4772, and slightly smaller than that of RZW_{stereo} , which is 0.1061. In addition, the average value of the mean *BERs* of our proposed RZW-SR is merely 0.0287. This value is much smaller than those of D-NOSE-RW, AUEW, and RZW_{DIBR} , which are 0.4218, 0.1759 and 0.1185, and slightly smaller than that of RZW_{stereo} , which is 0.0312. These results demonstrate that copyright identification of our proposed RZW-SR is much more reliable than those of D-NOSE-RW, AUEW, and RZW_{DIBR} and slightly better than that of RZW_{stereo} when the copyrights of 2D frames and depth maps are the same.

In addition, only our proposed RZW-SR and RZW_{DIBR} can protect these two components individually when the copyrights of 2D frames and depth maps are different. In contrast, D-NOSE-RW and AUEW only

protect the depth maps, whereas RZW_{stereo} only protects the 2D frames. Therefore, $RZW\text{-SR}$ and RZW_{DIBR} are more flexible and can better satisfy the requirements for protecting DIBR 3D videos than the other three schemes. Moreover, the maximal mean BER s of 2D frames and depth maps of our proposed $RZW\text{-SR}$ are 0.1783 and 0.1700. These values are much smaller than those of RZW_{DIBR} , which are 0.4981 and 0.4942. The average BER values of our proposed $RZW\text{-SR}$ are merely 0.0619 and 0.0628. These values are also much smaller than those of RZW_{DIBR} , which are 0.1308 and 0.1706. These results demonstrate that the copyright identification of our proposed $RZW\text{-SR}$ is more flexible than those of D-NOSE-RW, AUEW and RZW_{stereo} to better satisfy the requirements for protecting DIBR 3D videos and much more reliable than the copyright identification of RZW_{DIBR} .

TABLE 7. Mean BER s of different schemes

	D-NOSE-RW	AUEW	RZW_{stereo}	RZW_{DIBR} [30]			Our proposed $RZW\text{-SR}$		
	[42] (Depth map)	[29] (Depth map)	[45] (2D frame)	2D frame	Depth map	Fuse together	2D frame	Depth map	Fuse together
GB 9×9	0.5260	0.0000	0.0103	0.0195	0.0597	0.0144	0.0435	0.0216	0.0144
GB 15×15	0.5260	0.0000	0.0103	0.0206	0.0613	0.0077	0.0435	0.0216	0.0144
AF 9×9	0.5467	0.0007	0.0422	0.0444	0.0922	0.0384	0.0822	0.0360	0.0250
AF 15×15	0.5385	0.4731	0.0738	0.0663	0.1184	0.0578	0.1075	0.0478	0.0331
MF 9×9	0.5381	0.0009	0.0398	0.0336	0.0728	0.0247	0.0605	0.0172	0.0134
MF15×15	0.5483	0.4590	0.0625	0.0573	0.1069	0.0461	0.0818	0.0217	0.0171
CC -30	0.3691	0.0005	0.0273	0.0144	0.0408	0.0083	0.0210	0.0217	0.0106
CC +30	0.3381	0.1319	0.0019	0.0277	0.0947	0.0233	0.0319	0.0815	0.0229
CB -30	0.3909	0.0277	0.0218	0.0264	0.0483	0.0155	0.0698	0.0786	0.0369
CB +30	0.3927	0.1343	0.0312	0.0239	0.1022	0.0197	0.0595	0.1068	0.0382
GT $\gamma=0.6$	0.3915	0.0001	0.0042	0.0492	0.0659	0.0375	0.0463	0.0473	0.0234
GT $\gamma=1.4$	0.3872	0.0162	0.0291	0.0414	0.0558	0.0178	0.0367	0.0425	0.0197
GN 0.005	0.7233	0.1615	0.0753	0.0180	0.0422	0.0106	0.0424	0.0922	0.0291
GN 0.01	0.7259	0.4184	0.1061	0.0206	0.0464	0.0134	0.0632	0.1197	0.0413
LI 32×32	0.0659	0.0009	0.0255	0.2075	0.2797	0.1823	0.0000	0.0115	0.0000
LI 64×64	0.1309	0.0059	0.0171	0.2919	0.3459	0.2648	0.0475	0.0451	0.0231
RS 1/2	0.5425	0.0000	0.0007	0.0141	0.0347	0.0067	0.0329	0.0147	0.0101
RS 1/5	0.4855	0.0004	0.0007	0.0139	0.0342	0.0075	0.0643	0.0220	0.0164
CR 5%	0.2027	0.1086	0.0252	0.1578	0.3308	0.1570	0.0459	0.0650	0.0269
CR 10%	0.4339	0.2139	0.0203	0.2330	0.3625	0.2236	0.0782	0.1099	0.0457
RT 45	0.4896	0.5873	0.0355	0.4567	0.4742	0.4394	0.1422	0.1458	0.0719
RT 90	0.5224	0.5820	0.0263	0.4898	0.4867	0.4678	0.1783	0.1700	0.0870
FL Vertical	0.5561	0.5826	0.0000	0.4981	0.4942	0.4772	0.0112	0.0180	0.0069
FL Horizontal	0.5747	0.5863	0.0602	0.4906	0.4895	0.4720	0.0105	0.0178	0.0066
FR 5%	0.0202	0.0406	0.0324	0.0325	0.0441	0.0180	0.0943	0.1638	0.0598
FD 5%	0.0000	0.0422	0.0315	0.0519	0.0509	0.0298	0.1153	0.0942	0.0518

Average value	0.4218	0.1759	0.0312	0.1308	0.1706	0.1185	0.0619	0.0628	0.0287
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TABLE 8. Mean *BERs* of RZW-SR when utilizing depth maps, utilizing synthesized frames, and fusing them

	Depth map	Baseline distance=5% frame width				Baseline distance=7% frame width			
		Synthesized	Fuse	Synthesized	Fuse	Synthesized	Fuse	Synthesized	Fuse
		frame (left)	together	frame (right)	together	frame (left)	together	frame (right)	together
Without attack	0.0000	0.0495	0.0000	0.0492	0.0000	0.0670	0.0000	0.0670	0.0000
GB 9×9	0.0216	0.0692	0.0114	0.0695	0.0115	0.0838	0.0119	0.0844	0.0120
GB 15×15	0.0216	0.0693	0.0114	0.0695	0.0115	0.0838	0.0119	0.0844	0.0120
AF 9×9	0.0360	0.0977	0.0267	0.0975	0.0267	0.1082	0.0272	0.1089	0.0270
AF 15×15	0.0478	0.1182	0.0385	0.1180	0.0389	0.1265	0.0391	0.1264	0.0391
MF 9×9	0.0172	0.0799	0.0086	0.0974	0.0085	0.0928	0.0088	0.0939	0.0087
MF15×15	0.0217	0.0950	0.0136	0.0805	0.0136	0.1053	0.0138	0.1073	0.0135
CC -30	0.0217	0.0578	0.0111	0.0581	0.0111	0.0744	0.0117	0.0738	0.0116
CC +30	0.0815	0.0645	0.0432	0.0639	0.0430	0.0801	0.0494	0.0786	0.0493
CB -30	0.0786	0.0914	0.0563	0.0905	0.0560	0.1044	0.0598	0.1029	0.0589
CB +30	0.1068	0.0824	0.0590	0.0820	0.0589	0.0944	0.0646	0.0941	0.0643
GT $\gamma=0.6$	0.0473	0.0704	0.0305	0.0701	0.0305	0.0846	0.0321	0.0842	0.0326
GT $\gamma=1.4$	0.0425	0.0629	0.0264	0.0641	0.0263	0.0782	0.0279	0.0789	0.0277
GN 0.005	0.0922	0.0676	0.0477	0.0695	0.0492	0.0832	0.0530	0.0839	0.0543
GN 0.01	0.1197	0.0834	0.0625	0.0847	0.0644	0.0966	0.0686	0.0976	0.0705
LI 32×32	0.0115	0.0495	0.0017	0.0492	0.0015	0.0670	0.0019	0.0670	0.0018
LI 64×64	0.0451	0.0772	0.0282	0.0755	0.0278	0.0918	0.0294	0.0895	0.0294
RS 1/2	0.0147	0.0630	0.0053	0.0626	0.0052	0.0788	0.0055	0.0785	0.0055
RS 1/5	0.0220	0.0841	0.0135	0.0837	0.0132	0.0970	0.0137	0.0971	0.0137
CR 5%	0.0650	0.0769	0.0452	0.0765	0.0457	0.0926	0.0485	0.0916	0.0489
CR 10%	0.1099	0.1017	0.0701	0.1014	0.0700	0.1148	0.0749	0.1144	0.0753
RT 45	0.1458	0.1504	0.1056	0.1547	0.1085	0.1568	0.1079	0.1615	0.1104
RT 90	0.1700	0.1811	0.1289	0.1860	0.1302	0.1855	0.1306	0.1907	0.1317
FL Vertical	0.0180	0.0405	0.0077	0.0584	0.0082	0.0585	0.0081	0.0753	0.0084
FL Horizontal	0.0178	0.0508	0.0078	0.0504	0.0075	0.0679	0.0080	0.0675	0.0078
FR 5%	0.1638	0.1096	0.0896	0.1088	0.0895	0.1205	0.0960	0.1194	0.0961
FD 5%	0.0942	0.1292	0.0787	0.1298	0.0798	0.1382	0.0798	0.1397	0.0811
Average value	0.0628	0.0842	0.0381	0.0852	0.0384	0.0975	0.0402	0.0985	0.0404

Table 8 shows that the mean *BERs* when utilizing synthesized frames are still very small, with maximal values of 0.1811, 0.1860, 0.1855, and 0.1907 and average values of 0.0842, 0.0852, 0.0975, and 0.0985. For the synthesized frames without attacks, the *BERs* are as small as 0.0495, 0.0492, 0.0670 and 0.0670. In addition, the mean *BERs* when fusing the synthesized frames and depth maps are also just slightly larger than when fusing the original 2D frames and depth maps, with maximal values of 0.1289, 0.1302, 0.1306, and 0.1317 and average values of 0.0381, 0.0384, 0.0402, and 0.0404. These results demonstrate that copyright

identification of our proposed RZW-SR when utilizing (fusing) synthesized frames is still remarkable and just slightly worse than utilizing (fusing) original 2D frames. In addition, the *BERs* when fusing the synthesized frames and depth maps are smaller than those when only utilizing synthesized frames or depth maps, which is consistent with the results listed in Table 6. These results demonstrate that the attention-based fusion also enhances the performances of copyright identification under DIBR distortions with various attacks.

4.5 Evaluation of computational complexity

In this section, the computational complexity of our proposed RZW-SR is evaluated and discussed. Our proposed RZW-SR consists of three phases: the copyright registration phase, retrieval phase and copyright identification phase. The first phase is off-line, and the other two phases are on-line. The mean execution CPU times of different functions in different phases for one 3D video clip are tested over all of the 200 video clips. The results are compared with the other two state-of-the-art zero-watermark schemes, which are RZW_{stereo} [45] and RZW_{DIBR} [30], as shown in Table 9. The experiment in this section is executed on an Intel® Core™ i7-7700HQ Processor (4 cores at 2.80 GHz) with 32 GB of RAM via a MATLAB implementation.

TABLE 9. Mean execution times (s) of different functions of different schemes for one video clip

				RZW _{stereo} [45]	RZW _{DIBR} [30]	Our proposed RZW-SR	
Off-line	Registration phase	Feature extraction	2D frame	1.57×10 ¹	4.49×10 ⁻²	5.36×10 ⁻¹	
			Depth map	NA	3.75×10 ⁻²	5.27×10 ⁻¹	
		Generation of master and ownership shares	2D frame	2.74×10 ⁻⁵	1.65×10 ⁻⁴	3.60×10 ⁻³	
			Depth map	NA	1.59×10 ⁻⁴	3.59×10 ⁻³	
	On-line	Retrieval phase		2D frame	NA	NA	3.09×10 ⁻³
			Depth map	NA	NA	3.07×10 ⁻³	
			Fusion function	NA	NA	7.50×10 ⁻⁴	
Identification phase		Feature extraction	2D frame	1.51×10 ¹	4.37×10 ⁻²	5.28×10 ⁻¹	
			Depth map	NA	3.65×10 ⁻²	5.21×10 ⁻¹	
		Copyright information recovery and identification	2D frame	2.71×10 ⁻⁵	2.26×10 ⁻⁴	5.50×10 ⁻³	
			Depth map	NA	2.25×10 ⁻⁴	5.40×10 ⁻³	
				Fusion function	NA	6.15×10 ⁻⁷	9.03×10 ⁻⁶

Although the framework of our proposed scheme is slightly more complicated due to the design of the novel retrieval phase, the additional mean CPU execution time of the retrieval phase is only 6.91×10^{-3} s (3.09×10^{-3} s + 3.07×10^{-3} s + 7.50×10^{-4} s), which only occupies 0.32% of the total cost and is insignificant

compared with the mean CPU execution time of feature extractions, as shown in Table 9. Moreover, the use of the retrieval phase is necessary because it ensures the copyright identification accuracy when processing large-scale videos, which cannot be achieved by the other two zero-watermark schemes.

In addition, the most time-consuming functions of zero-watermark schemes are the feature extractions, which occupy almost 99% of the total costs (99.99% for RZW_{stereo} , 99.51% for RZW_{DIBR} and 98.83% for $RZW\text{-SR}$). Therefore, the mean CPU execution time is mainly determined by the computational complexity of feature extraction. Although the CPU execution times of feature extraction in RZW_{DIBR} [30] are shorter than those of RZW_{stereo} [45] and our proposed $RZW\text{-SR}$, the robustness of the simple 2D-DCT-based feature in RZW_{DIBR} is extremely poor against geometrical attacks such as cropping, rotation, and flipping, and the copyright identification using RZW_{DIBR} will fail under these attacks, as shown in Table 7. Therefore, it is necessary to design a more robust and complicated feature to ensure higher copyright identification reliability. Both the features in RZW_{stereo} and our proposed $RZW\text{-SR}$ guarantee the copyright identification reliability under signal, geometrical and temporal attacks. Compared with RZW_{stereo} , the CPU execution times for extracting our designed feature are much shorter (less than 1/10 of those of RZW_{stereo}), and our designed feature is much more discriminative.

In summary, our proposed $RZW\text{-SR}$ ensures sufficient copyright identification accuracy and reliability with acceptable CPU execution time and thus achieves better trade-off between the DRM performance and computational complexity than the two state-of-the-art zero-watermark schemes

4.6 Qualitative comparisons with current state-of-the-art schemes

In this section, qualitative comparisons with other state-of-the-art watermark schemes are conducted in terms of 5 aspects: 1) reliability of the copyright identification, 2) accuracy of the copyright identification, 3) distortion of DIBR 3D video, 4) involvement of similarity-based retrieval, and 5) independence of the copyrights of the 2D frames and depth maps. The comparison results are shown in Table 10.

TABLE 10. Qualitative comparisons with other schemes

	2D frame-based	Depth map-based	Zero-watermark		Our proposed
	watermark	watermark	RZW_{Stereo}	RZW_{DIBR}	$RZW\text{-SR}$
Reliability	Sufficient	Insufficient	Sufficient	Sufficient	Sufficient
Accuracy	Sufficient	Sufficient	Insufficient	Insufficient	Sufficient
Distortion of 3D video	Not free	Free	Free	Free	Free
Similarity-based retrieval	No	No	No	No	Yes
Independence of copyrights	No	No	No	Yes	Yes

As shown in Table 10, our proposed RZW-SR outperforms other state-of-the-art schemes in terms of all 5 of these aspects. In contrast to 2D frame-based watermark schemes [1-3, 6-7, 9, 13, 20, 23, 26, 31, 34, 36, 47], RZW-SR does not directly embed watermark information into 2D frames, which avoids the introduction of distortion into the 3D videos. Compared with the depth map-based watermark schemes [8, 28-29, 33, 37-38, 42], RZW-SR is more robust against various video attacks and thus can provide more reliable copyright identification. Compared with the other two zero-watermark schemes, which are RZW_{Stereo} [45] and RZW_{DIBR} [30], RZW-SR designs an effective similarity-based retrieval mechanism, and their relevant ownership can be obtained precisely according to the retrieval results. Therefore, the accuracy of copyright identification in RZW-SR is ensured when processing large-scale videos, which cannot be achieved by other zero-watermark schemes. Last but not least, compared with 2D frame-based watermark schemes, depth map-based watermark schemes and RZW_{Stereo} , only RZW_{DIBR} and our proposed RZW-SR have designed flexible mechanisms for copyright identification to protect the 2D frames and depth maps separately and independently when the copyrights of 2D frames and depth maps are different.

5. Conclusions

In this paper, a novel RZW-SR is proposed by fusing the similarity-based retrieval and zero-watermark technique. It is the first scheme that fuses these two techniques to protect DIBR 3D videos. Our analytical and experimental results have demonstrated that our proposed RZW-SR possesses the following merits. First, RZW-SR does not directly embed the copyright information into the 3D videos. Therefore, RZW-SR can avoid content distortion, which outperforms 2D frame-based watermark schemes. Second, RZW-SR achieves significant robustness against signal, geometrical, and temporal attacks and DIBR distortions by utilizing temporal information and designing invariant video features, which outperforms depth map-based watermark schemes. Third, RZW-SR can retrieve and protect 2D frames and depth maps of 3D videos independently or simultaneously by designing flexible mechanisms based on attention-based fusion. It better satisfies different DRM requirements of 3D videos compared to 2D frame-based schemes, depth map-based schemes and RZW_{Stereo} . Finally, RZW-SR can obtain the ownership relevant to 3D videos precisely and reliably even when processing large-scale DIBR 3D videos by designing an effective similarity-based retrieval mechanism, which cannot be achieved by the existing zero-watermark schemes for DIBR 3D videos. In the future, we will further explore and make use of the relationships between video frames, such as the frame variations, to further enhance the feature distinguishability. In addition, exploration of the possibility of applying our proposed scheme to protect medical volume data, such as 3D computed tomography (CT) imaging, magnetic

resonance imaging (MRI) and optical coherence tomography (OCT) imaging, is also included in our future works.

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