Kalman filter-based prediction refinement and quality enhancement for geometry-based point cloud compression

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Abstract—A point cloud is a set of points representing a three-dimensional (3D) object or scene. To compress a point cloud, the Motion Picture Experts Group (MPEG) geometry-based point cloud compression (G-PCC) scheme may use three attribute coding methods: region adaptive hierarchical transform (RAHT), predicting transform (PT), and lifting transform (LT). To improve the coding efficiency of PT, we propose to use a Kalman filter to refine the predicted attribute values. We also apply a Kalman filter to improve the quality of the reconstructed attribute values at the decoder side. Experimental results show that the combination of the two proposed methods can achieve an average Bjøntegaard delta bitrate of -0.48%, -5.18%, and -6.27% for the Luma, Chroma Cb, and Chroma Cr components, respectively, compared with a recent G-PCC reference software.

Index Terms—point clouds, predictive coding, Kalman filter

I. INTRODUCTION

With the rapid development of 3D sensing technologies, such as laser scanning and oblique photogrammetry, point clouds have become an important source of data [1] [2]. High-precision point clouds are widely used in 3D digital modeling of smart cities, autonomous driving, heritage protection, etc. Due to the huge data volume of point clouds, efficient compression is critical.

To compress point clouds, MPEG proposed a video-based compression platform (V-PCC) [3] and a geometry-based compression platform (G-PCC) [4]. Compared to V-PCC, G-PCC is more appropriate for sparse point clouds [5]. In this paper, we focus on G-PCC.

G-PCC can use three transforms for coding the attribute information of the points: region adaptive hierarchical transform (RAHT) [6], predicting transform (PT) [7], and lifting transform (LT) [8]. The latter two are based on Level of Details (LODs) [7] as shown in Fig. 1. Using a set of fixed

distances $(d_l)_{l=0\dots L-1}$ specified by the user, the point cloud is first re-organized into a set of refinement levels $(R_l)_{l=0\dots L-1}$. Then, the l th level of detail, denoted by LOD_l , is obtained by taking the union of the refinement levels $R_0, R_1, \dots, R_l$ (i.e., $LOD_l = \bigcup_{i=0}^l R_i$). Next, multiple predictor candidates for the current coding point are selected based on its k nearest neighbors. The best predictor is finally determined with rate-distortion optimization [4]. Points in an LOD are predicted successively according to the generating order of LOD. Then the residuals are calculated as the difference between the original attribute and the predicted attribute and quantized before entropy coding. Since the reconstructed attribute of the current point is used to predict the attribute of the subsequent points, prediction errors may propagate and accumulate. An overview of the point cloud attribute compression procedure for PT is illustrated in Fig. 2. Based on the point-by-point prediction structure of PT in G-PCC, we propose a Kalman filter-based prediction refinement method to improve the prediction accuracy and also propose a Kalman filter-based quality enhancement method for the reconstructed point cloud after decoding.

The remainder of the paper is organized as follows. Section II discusses related work. Section III presents the proposed method. Experimental results and conclusions are given in Section IV and V, respectively.

II. RELATED WORK

The architecture of G-PCC is shown in Fig. 3. In the encoder, point positions (geometry information) are coded first. Then, the attributes are coded based on the reconstructed geometry. For PT-based attribute coding, the Manhattan or the Euclidean distance is used to generate the LOD order and select the best predictor for each point in an LOD. Compared

Fig. 1. LOD generation in G-PCC.

Fig. 2. Overview of attribute compression for PT.

with RAHT and LT, the prediction accuracy of PT still needs to be improved. Yea *et al.* [9] applied the bilateral filter as an in-loop-filter for PT. Sugio *et al.* [10] proposed to select the best predictor with rate-distortion optimization. Ma *et al.* [11] proposed to smooth the attributes of neighbouring points before prediction. Zhang *et al.* [12] added a modification parameter called *intraPredictionWeight* to set the optimal weights of neighbouring points.

To further improve the coding efficiency as well as improve the reconstruction quality of point clouds, post-processing-based quality enhancement is also important. The existing point cloud enhancement methods are mainly aimed at geometric distortion. Alexa *et al.* [13] used the points at the vertices of the Voronoi diagram to interpolate in the local tangent space to complete the upsampling. Lipman *et al.* [14] proposed a point cloud upsampling method based on the locally-optimal-projection operator for surface reconstruction. However, there is no research focusing on enhancing the reconstruction quality of the attribute.

In this paper, we proposed to use a Kalman filter to improve the prediction accuracy during the encoding procedure and to improve the reconstruction quality of attributes after decoding.

III. PROPOSED METHOD

In this section, we first provide the basic principles of the Kalman filter and then describe the details of the proposed method.

A. Kalman filters

The Kalman filter [15] is an efficient recursive filter. It can reduce the system prediction error gradually and is particularly suitable for stationary random signals. The Kalman filter uses

Fig. 3. Framework of G-PCC encoder.

Fig. 4. Basic Kalman filter framework.

an estimation of the previous state to find the optimal value of the current state. As shown in Fig. 4, the Kalman filter consists of three main parts: prediction, correction and update. It requires two important input variables: the measured value z_t and the initial prediction value $\hat{x}'_t$.

a) *Prediction process*: The initial prediction $\hat{x}'_t$ of the signal value $\hat{x}_t$ at time t can be represented by a linear function of the previous signal value $\hat{x}_{t-1}$, i.e.,

$$\hat{x}'_t = \mathbf{A}\hat{x}_{t-1} + \mathbf{w}_{t-1}, \quad (1)$$

where $\mathbf{A}$ is the state transition matrix (usually an identity matrix) and $\mathbf{w}_{t-1}$ represents noise.

To calculate the Kalman gain (the minimum variance between the original and the predicted values) and correct the initial prediction, the prediction error covariance matrix $\mathbf{P}'_t$ of

Fig. 5. Application of the Kalman filter to one point of a point cloud.

Fig. 6. System diagram of the proposed algorithm. Std(Point Cloud) denotes the standard deviation of the attributes in the R, G, B components. T is a threshold set empirically to 40.

$\hat{x}'_t$ is calculated first as

$$P'_t = AP_{t-1}A^T + Q, \quad (2)$$

where P_{t-1} is the prediction error covariance matrix of $\hat{x}_{t-1}$ and Q is the covariance matrix of the process excitation noise whose initial value is set empirically. The Kalman gain K_t at time t can then be written as

$$K_t = P'_t H^T (H P'_t H^T + R)^{-1}, \quad (3)$$

where H is the state observation matrix, which is usually the identity matrix, and R is the matrix of the inaccuracy of the system, whose initial value is set empirically.

b) Correction process: By using the measured value z_t and the Kalman gain K_t , $\hat{x}'_t$ can be refined as

$$\hat{x}_t = \hat{x}'_t + K_t (z_t - H\hat{x}'_t), \quad (4)$$

c) Update process: Finally, the error covariance is matrix updated as

$$P_t = (I - K_t H) P'_t, \quad (5)$$

where I denotes the identity matrix. The updated matrix P_t is then used to filter the signal at time $(t+1)$.

B. Kalman Filter-based prediction refinement

We consider point clouds as discrete-time signals. The Kalman filter for one point in a point cloud is shown in Fig. 5. The reconstructed attribute of the previous point is used as the measured value z_t of the current point, and the PT predicted attribute of the current point is taken as the prediction $\hat{x}'_t$ of the filter. Then, by calculating the Kalman gain K_t of the current point and the measured value z_t , we can refine the prediction of the current point to get the filtered value $\hat{x}_t$, and then update the covariance matrix to calculate the Kalman gain K_{t+1} for the next point. The above operation is iterated until all points are traversed.

Fig. 6 shows a block diagram of the entire point cloud system. The following operations are based on the order of refinement levels (i.e., $R_0, R_1 \dots R_{N-1}$, where N is the number of refinement levels), as shown in Fig. 1. To improve the results, we first determine whether the Kalman filter needs to be applied to the color component by checking its standard

deviation. If the standard deviation is large (indicating the signals are not stationary enough), the efficiency of the Kalman filter will be reduced. In this case, we disable the Kalman filter. The standard deviation threshold is set empirically to 40. Because the number of points is very small in the first seven refinement levels ($R_0 \sim R_6$), the points of the first seven refinement levels are taken as a whole to calculate the standard deviation. For each subsequent refinement level (i.e., $R_l, l > 6$), the same check is also done to decide whether to use the Kalman filter.

To further improve the results, we also directly transmit to the receiver the original attributes of a number of points from each refinement level. These points are selected as follows. If there are fewer than eight points in the refinement level, we select all of them. Otherwise, we select the eight points $P_1, P_{1+\lfloor M/8 \rfloor}, P_{1+2\lfloor M/8 \rfloor}, \dots, P_{1+7\lfloor M/8 \rfloor}$, where the indices of the points correspond to the refinement level-based order, and M is the number of points in this refinement level. This is because:

- The Kalman filter can produce more accurate results when the measured values are close to the original values.
- The transmitted original attribute can also be used as the reconstructed attribute to improve the quality of the reconstructed point clouds.

Fig. 7. System diagram of the proposed algorithm for improving the quality of the attribute of the reconstructed point cloud.

C. Kalman Filter-based post-processing

Furthermore, we also use a Kalman filter to enhance the quality of the reconstructed attributes. The system diagram is shown in Fig. 7. When the coding distortion is not large, the benefit of the Kalman filter is not obvious. Therefore, the proposed method is only used for quantization parameters (QPs) larger than or equal to 22. As the texture values vary more in the luminance component than in the Cb and Cr

components, the Kalman filter is only used for the Cb and Cr components.

During the Kalman filtering procedure, the average of the reconstructed attributes of the first three points is used as the measured value z_t , while the reconstructed attribute of the current point is used as the predicted value $\hat{x}_t'$. The filtering is used to filter the Cb and Cr components of the initial reconstructed attribute of the current point, while the Y component is left unchanged. The filtered value is used in the reconstructed point cloud.

IV. EXPERIMENTAL RESULTS

We implemented the proposed methods in G-PCC test model TMC13 version 11.0 (TMC13V11) [16] and conducted experiments under the CY configuration of the common test conditions of MPEG G-PCC [17]. The computer used for the experiment has an Intel I7-8700K processor and 32GB RAM. Experiments were conducted for 21 point clouds from the Cat1-A and Cat1-B datasets provided by MPEG. To evaluate the performance, we used the Bjontegaard delta(BD)-rate [18] and the complexity ratio. The BD-rate gives the average bitrate reduction of the proposed method compared to TMC13V11 at the same reconstructed quality (a negative BD-rate corresponds to a reduction in bitrate). The complexity ratio is the ratio of the encoding time (resp. decoding time) of the proposed method to that of TMC13V11.

Table I compares the performance of the proposed Kalman filter-based prediction refinement to TMC13V11. We can see that an average -0.46%, -2.82%, -3.64% BD-rate can be achieved for the Luma, Chroma Cb, and Chroma Cr components, respectively. We can also see that the decoding complexity of the proposed method is slightly increased.

Table II shows the results for the proposed Kalman filter-based post-processing for point cloud quality enhancement. We can see that an overall average -0.0%, -1.93%, -2.16% BD-rate gain can be achieved for the Luma, Chroma Cb, and Chroma Cr components, respectively.

Table III shows that combining the proposed two methods is advantageous as it allows to increase the average BD-rate gain to -0.48%, -5.18%, -6.27% for the Luma, Chroma Cb, and Chroma Cr components, respectively. Fig. 8 compares the visual quality of the reconstructed point clouds. We can see that the reconstruction of the clothes of *loot_viewdep_vox12* with the proposed methods is better than with TMC13V11.

As the Kalman filter is an optimal state estimation method [15], the refined prediction is more accurate than the original PT, and the reconstruction quality can also be improved by the Kalman filter-based post-processing. Since the luminance information is not stable enough, as the attribute values vary more in the luminance than in the Cb and Cr components, and the Kalman filter is more effective for stationary signals, the coding efficiency for the luminance is not as large as for the Cb and Cr components.

V. CONCLUSIONS

We proposed a Kalman filter-based prediction refinement technique and quality enhancement method for point cloud

TABLE I
AVERAGE BD-RATE GAIN OF THE METHOD PROPOSED IN SECTION III-B
COMPARED WITH THE G-PCC TEST MODEL

Dataset category	BD-rate for attributes (%)			Complexity Ratio(%)	
	Luma	Chroma Cb	Chroma Cr	Encoding	Decoding
Cat1-A average	-0.66	-3.29	-4.19	101	101
Cat1-B average	-0.08	-1.90	-2.54	101	101
Overall average	-0.46	-2.82	-3.64	101	101

TABLE II
AVERAGE BD-RATE GAIN OF THE METHOD PROPOSED IN SECTION III-C
COMPARED WITH THE G-PCC TEST MODEL

Dataset Category	BD-rate for attributes (%)			Complexity Ratio(%)	
	Luma	Chroma Cb	Chroma Cr	Encoding	Decoding
Cat1-A average	0	-1.45	-1.77	100	101
Cat1-B average	0	-2.88	-2.93	100	101
Overall average	0	-1.93	-2.16	100	101

TABLE III
OVERALL AVERAGE BD-RATE GAIN COMPARED WITH THE G-PCC TEST
MODEL.

Dataset Category	BD-rate for attributes (%)			Complexity Ratio(%)	
	Luma	Chroma Cb	Chroma Cr	Encoding	Decoding
Cat1-A average	-0.69	-5.31	-6.54	101	102
Cat1-B average	-0.08	-4.94	-5.72	101	102
Overall average	-0.48	-5.18	-6.27	101	102

Fig. 8. Visual quality comparison for *loot_viewdep_vox12*.

compression. In the prediction refinement method, the standard deviation of the attributes of the points to be encoded is calculated to decide whether using the Kalman filter is beneficial. In the quality enhancement method, only the Chroma Cb and Chroma Cr components are filtered when QP is large. Experimental results showed that -0.48%, -5.18%, -6.27% BD-rate gains can be achieved for the Luma, Chroma Cb, and Chroma Cr components, respectively, compared with the state-of-the-art MPEG G-PCC test model.

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