Fast Person Identification Using JPEG2000 Compressed ECG Data

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***Abstract*—The use of electrocardiogram (ECG) signals in biometric systems has been an active research topic for over a decade. In wireless telecardiology applications, compressed ECG packets are often required for efficient transmission and storage purposes. Nonetheless, compressed ECG data must be decompressed first before applying existing biometric techniques that work on the original signal. To achieve a faster patient care, we propose a new biometric technique which performs person identification in compressed-domain using one-lead ECG signals. First, we apply a preprocessor which converts one-dimensional (1-D) ECG signals to 2-D image matrices and compresses them by the JPEG2000 image coding standard. Features relating to ECG morphology were extracted directly from the JPEG2000 code-stream and then applied for indexing person identity by texture content in a known enrollment database. Experiments on standard ECG databases demonstrate the validity of the proposed compressed-domain ECG biometric system with an accuracy of 95.72%.**

Keywords–ECG Biometric; Person Identification; JPEG2000 Image Coding Standard.

I. INTRODUCTION

Electrocardiogram (ECG) signal is a recording of the electrical activity of the heart and is a clinical diagnosis tool for cardiac diseases. Typical features are linked to the peaks and time durations of the P-QRS-T waves representing the heart activity in terms of depolarization and repolarization of the atria and ventricles [1]. In wireless telecardiology applications, ECG data forwarded by the user to the hospital needs to be verified and authenticated to guard against spoof attack. Recently, some proposals have suggested the possibility of using ECG as a new biometrics modality for person identification [2]-[9]. Comparing with other biometric traits such as fingerprints and voice, the ECG of a human is more universal and secure. The validity of using ECG biometric is supported by the fact that ECG can only be obtained through a sensor placed around the user and forgery is difficult as the unique shape of the ECG signal is affected by the physiological and geometrical differences of the heart in different individuals.

Basically, ECG biometrics can be achieved by comparing the enrollment ECG template and recognition ECG template. Based on the features that are extracted from ECG signals, we can classify ECG biometric methods as fiducial-based [2]-[5], non fiducial-based [6]-[8], or a hybrid [9]. Among them, Discrete Wavelet Transform (DWT) techniques have shown effective for extracting discriminative features in ECG biometric recognition [6][7]. Irrespective of underlying methods used for the generation of the templates, most of the existing ECG biometrics work on uncompressed raw ECG signals [2]-[9]. However, in remote telecardiology scenarios, ECG data are often kept in compressed format for efficient transmission and storage purposes. Many ECG data compression methods have been proposed, including direct time-domain methods and transformation methods [10][11]. Most of the ECG data compression methods adopt one-dimensional (1-D) representations for ECG signals and focus on the utilization of the intra-beat correlation between adjacent samples. Since the ECG signals have both intra- and inter-beat correlation, better algorithms have been proposed to get the most of benefit from both types of correlation [12][13]. These methods generally start with a preprocess which converts 1-D ECG signals to 2-D data arrays through the combined use of QRS detection and period normalization. The constructed 2-D ECG data arrays are then ready to be further compressed by the vector quantization [12] or the JPEG2000 image coding standard [13]. In such scenarios, then the compressed ECG data must be fully decompressed before applying existing biometric techniques. Apart from posing threat to the emergency patient, delay in authentication can be an unnecessary burden on the hospital system, as the hospital may have thousands of enrolled patients and decompression of all their ECG packets is an enormous work. This drawback can be avoided by directly reading the compressed ECG data to obtain unique features that can identify an individual. The key advantage of the proposed compressed-domain ECG biometric system is smaller template size and faster biometric matching compared with existing biometric systems. In addition, most of the literatures have concentrated their research on obtaining healthy subjects in their experiments. By contrast, we will look into the effects of diseased subjects on the recognition rate of an ECG biometric system.

The rest of this paper is organized as follows. Section II describes the ECG fundamentals and presents a preprocessor which converts 1-D ECG signals to 2-D image matrices. Section III gives an overview of the JPEG2000 encoding algorithm. Details of the algorithms for the proposed ECG biometric system are provided in Section IV. Section V presents the simulation results for the healthy and diseased subjects using standard ECG databases. Finally, Section VI gives our conclusions.

II. 2-D ECG COMPRESSION

To begin, we apply a preprocessor, which can be viewed as a cascade of two stages. In the first stage, the QRS complex in each heartbeat is firstly detected for segmenting and aligning 1-D ECG signals to 2-D image matrices and in the second stage, the constructed matrices are compressed by JPEG2000 [14]. Figure 1 shows the block diagram of the 2-D ECG compression scheme proposed by Bilgin [13].

A. ECG Data Sources

The ECG data for the experiments are obtained from the QT Database [15] that contains ECG recordings collected from healthy subjects and patients with various heart diseases. First, 10 healthy subjects from the MIT-BIH Normal Sinus Rhythm

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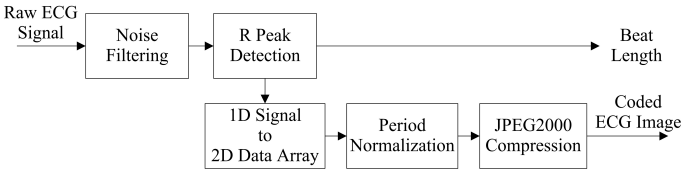

Figure 1. Block diagram of the ECG JPEG2000 compression scheme [13].

Database are used in the experiments and denoted as dataset D1. Subjects that are added to the system to determine the effects of the diseased ECG consist of 10 records from the MIT-BIH Arrhythmia Database, 10 records from the MIT-BIH Supraventricular Arrhythmia Database, and 10 records from the Sudden Cardiac Death Holter Database. For convenience, these three groups of diseased subjects are denoted as dataset D2, D3, and D4, respectively. Each of these records is 15 minutes in duration and are sampled at 250 Hz with a resolution of 11 or 12 bits/sample. The ECG waveform of a normal heartbeat consists of a P wave, a QRS complex, and a T wave [1]. The P wave corresponds to the sequential depolarization of the right and left atria. The QRS complex is produced when the ventricles depolarize and squeeze the blood from the right ventricle to the aorta. The T wave occurs due to ventricular repolarization. A typical representation of the ECG waveform is shown in Figure 2. It can be seen that an ECG signal tends to exhibit considerable similarity between adjacent heartbeats, along with short-term correlation between adjacent samples. Thus, by dividing an ECG signal into heartbeat segments with lengths equal to the beats, there should be a large correlation between individual segments.

B. 2-D Image Matrix Construction

ECG itself is 1-D in the time-domain, but can be viewed as a 2-D signal in terms of its implicit periodicity. The QRS complex is the most characteristic wave in an ECG waveform and hence, its peak can be used to identify each beat. First of all, raw ECG signals are filtered to remove various noises. Afterwards we apply the Biomedical Signal Processing Toolbox [16] to detect the R peak of each QRS complex. Then, an ECG signal is divided into heartbeat segments and each segment is stored as one row of a 2-D data array. Having constructed the data array as such, the intra-beat correlation is in the horizontal direction of the array and the inter-beat correlation is in the vertical direction. Since the heartbeat segments may have different lengths, each row of the data array is period normalized to a fixed length of $N_p = 200$ samples via cubic spline interpolation. This choice was based on the observation that the average heartbeat length is about 0.8 second, which corresponds to 200 samples for a 250-Hz sampling frequency. Accordingly, the original heartbeat length was represented with 9 bits and transmitted as side information. Finally, we proceed to construct image matrices of dimension 200×200 by gathering together 200 rows of the data array and normalizing the amplitude of each component to an integer ranging from 0 to 255. A typical example of an ECG image matrix is shown in Figure 3. The constructed gray-scale ECG image matrices are then ready to be further compressed by the JPEG2000 still image coding standard.

III. JPEG2000 ENCODING ALGORITHM

Although the JPEG2000 coding standard was originally developed for still image compression, its applicability to

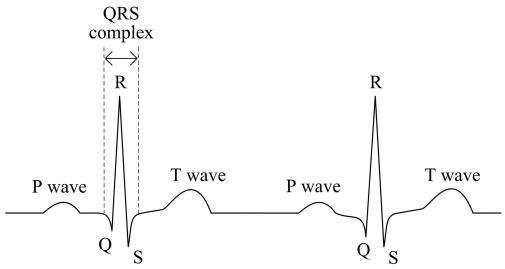

Figure 2. Typical ECG wave pattern in time-domain.

Figure 3. ECG image matrix for record sel17453m of the QT Database.

ECG data compression has been proposed in [13]. Compared with the original JPEG coding standard, the wavelet-based JPEG2000 provides advanced features in scalability and flexibility. In addition, JPEG2000 supports Region of Interest (ROI) coding so that different parts of an image can be coded with different fidelity. The JPEG2000 encoding process consists of the following operations: 1) a preprocessing step which includes tilling, DC-level shifting and color space transform, 2) 2-D DWT followed by quantization, and 3) entropy coding and bit-stream organization. The fundamental building blocks of JPEG2000 are shown in Figure 4. The encoder begins with a preprocessor which divides the source image into rectangular blocks called tiles. For each tile, the DC level of image samples is shifted to zero and color space transform is performed to decorrelate the color information. Then, the 2-D DWT is carried out for each color component of a tile. Successive dyadic decompositions are applied and each of these splits high and low frequencies in the horizontal and vertical directions into four subbands. Among them, the subband corresponding to the lowest frequency in the two directions is used as a starting point for the next decomposition. This process is repeated for N levels until no significant gains in compression efficiency can be obtained. In total, $(3N+1)$ subbands are obtained with respect to an N-level 2-D wavelet decomposition.

The 2-D DWT can be viewed as a cascade of 1-D DWT in the horizontal direction and 1-D DWT in the vertical direction. Specifically, the 1-D DWT is based on the lifting scheme described in [17]. First, source data $x[n]$ are split into even samples $s_0[n] = x[2n]$ and odd samples $d_0[n] = x[2n+1]$. Then, the detailed coefficients $d_i[n]$ and the approximation

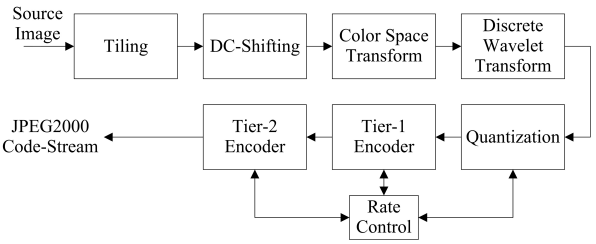

Figure 4. Fundamental building blocks of a JPEG2000 encoder [14].

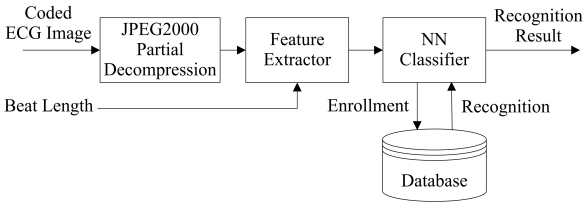

Figure 5. The proposed ECG biometric system.

coefficients $s_i[n]$ at the i-th iteration are calculated as follows:

$$d_i[n] = d_{i-1}[n] - \sum_k P_i[k] s_{i-1}[n-k], i = 1, 2, \ldots, N-1$$
$$s_i[n] = s_{i-1}[n] + \sum_k U_i[k] d_i[n-k], i = 1, 2, \ldots, N-1, \quad (1)$$

where P_i and U_i represent a predictor and an updater, respectively. Finally, both the detailed and approximation coefficients are normalized. For notational convenience, let $x_j(m,n)$ represent the wavelet coefficient located at position (m,n) in the j-th subband. After the 2-D DWT, a uniform quantizer is applied to quantize each wavelet coefficient $x_j(m,n)$ by an index $\bar{x}_j(m,n)$ as follows:

$$\bar{x}_j(m,n) = \text{sgn}(x_j(m,n)) \left\lfloor \frac{|x_j(m,n)|}{\Delta_j} \right\rfloor, \quad (2)$$

where Δ_j denotes the quantizer's step size. The last step in JPEG2000 compression consists in entropy coding with two tier encoders. In the tier-1 encoder, quantized indexes of each subband are split into code-blocks, which are then compressed using a context-based entropy coder. The tier-2 encoder truncates the bit-streams of each code-block to meet the targeted compression ratio, and combines them with additional headers to form the JPEG2000 code-stream.

IV. Proposed ECG Biometric Algorithm

Person identification is essentially a pattern recognition problem consisted of two stages: feature extraction and classification. Under the JPEG2000 framework, the person identification problem is analogous to a Content Based Image Retrieval (CBIR) problem. Concerning compressed-domain techniques, the JPEG2000 code-stream is subjected to partial decoding and then the energies from all subbands are used as the feature set. We also introduce a new method for feature extraction that involves the application of the Principal Component Analysis (PCA) for dimensionality reduction. In the classification stage, the query ECG image is compared with the enrollment database, and output the person identity that best matches the query with respect to some distance measurement criterion. Figure 5 shows the block diagram of the proposed ECG biometric system.

A. Feature Extraction in DWT Domain

Feature extraction is the first step in applying CBIR to ECG biometrics and one that conditions all the subsequent steps of system implementation. For arbitrary image databases of natural scenes, color and texture features are considered most important. Since 1-D ECG signals are converted to gray-scale images, we shall focus on the texture features that characterize smooth, coarse and regularity of the specific image. One effective tool to texture analysis is the DWT as it provides good time and frequency localization ability. Its multi-scale nature also allows the decomposition of an ECG into different scales, each of which represents particular coarseness of the signal. Furthermore, DWT coefficients in JPEG2000 can be obtained without involving a full decompression, as partial decoding of the JPEG2000 code-stream would suffice the needs. This is a favorable property as the inverse DWT and subsequent decoding processes could impose intensive computational burden. Different texture features such as energy, significance map, and intensity histogram at the output of wavelet filter-banks have been successfully applied to wavelet-based image retrieval [18]-[20]. In general, any measures that provide some degree of class separation should be included in the feature set. However, as more features are added, there is a trade-off between classification performance and computational complexity.

We began by using the energies from all subbands as a first step towards an efficient characterization of texture in compressed ECG images. This is because that the energy distribution along the frequency axis over scale and orientation has been shown effective for texture characterization in image retrieval [19][20]. For each subband, the reconstructed wavelet coefficients $\tilde{x}_j(m,n)$ are computed as follows:

$$\tilde{x}_j(m,n) = [\bar{x}_j(m,n) + r \cdot \text{sgn}(\bar{x}_j(m,n))] \cdot \Delta_j, \quad (3)$$

where $\bar{x}_j(m,n)$ represents the decoded quantizer indexes and the bias parameter r is set to be zero here. Then, the energy of the j-th subband is defined as

$$E_j = \frac{1}{M_j N_j} \sum_{m=1}^{M_j} \sum_{n=1}^{N_j} \tilde{x}_j^2(m,n), \quad (4)$$

where M_j and N_j represents the row and column dimension, respectively. Another feature of interest is the average time elapse between the current and previous R peaks, referred to as the RR-interval. Certain ECG arrhythmias, such as premature ventricular contraction and atrial premature beats, are related with premature heart beats that provide shorter RR-intervals than other types of ECG signals. Changes in the RR-interval plays an important role in characterizing these types of arrhythmias. Notice that the RR-interval can be calculated from the beat lengths which are transmitted as side information along with the JPEG2000 code-stream. In total, $(3N+2)$ features are used to form a Biometric Identification Vector (BIV), including the RR-interval and $(3N+1)$ subband energies.

The second feature set is obtained by applying PCA on the subband whose frequency is the lowest in both horizontal and vertical directions. This choice is based on the fact that human eyes are more sensitive to low frequency components than high frequency components. As one of the most commonly used dimension reduction techniques, PCA finds the most

representative set of projection vectors such that the projected samples retain the most information about the original data samples. To begin, the M wavelet coefficients in the lowest frequency subband of a training dataset are used to compute the covariance matrix $\mathcal{C}$. Following an eigenvalue decomposition, we obtain an eigenvalue matrix D and its corresponding eigenvector matrix V with its column vectors sorted in the descending order of eigenvalues. Finally, column vectors of V are used as a basis set for projection of the data in the directions of sorted eigenvectors. Let $\mathbf{x}_l$ represent the data vector consisting of M wavelet coefficients in the lowest frequency subband taken from the l-th ECG image. The PCA procedure can be expressed as

$$\mathcal{C} = \sum_{l=1}^{N_t} (\mathbf{x}_l - \bar{\mathbf{x}})(\mathbf{x}_l - \bar{\mathbf{x}})^T = VDV^T, \quad (5)$$

where N_t is number of ECG images used in the training dataset and $\bar{\mathbf{x}}$ represents the mean vector of all $\mathbf{x}_l$. Then, the data vector $\mathbf{x}_l$ is projected on the eigenvectors by taking the inner product according to $\mathbf{y}_l = V^T\mathbf{x}_l$. In this work, the PCA was applied on $M = 49$ coefficients of the lowest frequency subband and seven principal components were selected corresponding to retaining approximately 99% of the total variability in the training dataset. Together with the RR-interval, only eight features are used to form a BIV for the second feature set.

B. Enrollment and Recognition

The proposed person identification system can be divided into two stages: enrollment and recognition. During the enrollment stage, a number of BIVs of each enrolled user were taken as a representation of the user and enrolled into a database. In the recognition stage, the ECG signals of an unknown subject are acquired and then compressed by JPEG2000. Afterwards, the feature extraction procedure results in a query BIV to be compared with all the BIVs enrolled in the database. Accordingly, the system outputs the person identity of an enrolled BIV which best matches the query BIV with respect to a distance measurement criterion. In this work, the Standard Euclidean Distance (SED) is adopted to measure the respective similarity between the query BIV $\mathbf{q}$ and each enrolled BIV $\mathbf{e}$. Mathematically, the SED is denoted by $d_{\mathbf{q},\mathbf{e}}$ and can be expressed as

$$d_{\mathbf{q},\mathbf{e}} = \sqrt{\sum_{i=1}^{L} (\frac{\mathbf{q}(i) - \mathbf{e}(i)}{\sigma_i})^2}, \quad (6)$$

where L is the length of the BIV, $\mathbf{q}(i)$ and $\mathbf{e}(i)$ denote the i-th component in the corresponding BIV, and the scale factor σ_i represents the standard deviation computed from the i-th component of all enrolled BIVs. As the data belonging to the same class should be close in the feature space, a Nearest-Neighbor (NN) classifier is used to search for the minimum SED value and assigns its corresponding person identity as the recognition result.

V. Experimental Results

Computer simulations were conducted to evaluate the performance of the proposed compressed-domain approaches for person identification. Two ECG biometric systems based on JPEG2000, denoted by PA1 and PA2, are presented and investigated. They both applied a preprocessor for construction of the 2-D ECG image matrices in the JPEG2000 format and used an NN classifier for subsequent person identification. Unlike the PA1 which was performed using subband energy-based feature set, the PA2 extracted the wavelet coefficients from the lowest frequency subband and represented in a lower dimensional space using PCA. 10 normal subjects and 30 diseased subjects from the QT Database are chosen to represent a wide variety of QRS and ST-T morphologies. The JPEG2000 codec used here was the open-source software JasPer version 1.900.0 [21]. ECG images were compressed in a lossy mode using Daubechies 9/7 filter with 5-level of decomposition, while the dimension of each tile and code-block is set to be 200×200 and 64×64, respectively. Besides, the parameter value of coding rate ρ is set to be 0.15 and 0.08 in order to achieve the compression ratio of 10 and 20, respectively.

A preliminary experiment was first conducted on normal and diseased ECG signals to examine the performance of 2-D compression by JPEG2000 [13]. Typically, the performance is evaluated in terms of the compression ratio (CR) and the percent root mean square difference (PRD). The CR is defined as

$$\text{CR}=\frac{N_{ori}}{N_{com}}, \quad (7)$$

where N_{ori} and N_{com} represent the total number of bits required for the original and compressed ECG data, respectively. The PRD is used to evaluate the reconstruction distortion and is defined by

$$\text{PRD}(\%) = \sqrt{\frac{\sum_{k=1}^{K}[x_{ori}(k) - x_{rec}(k)]^2}{\sum_{k=1}^{K} x_{ori}(k)^2}} \times 100, \quad (8)$$

where K is the total number of original samples in the record and x_{ori} and x_{rec} represent the original and reconstructed ECG signals, respectively. Table I presents the average results for 2-D compression of various ECG records using JPEG2000 with coding rate $\rho = 0.15$ and $\rho = 0.08$. As should be expected, the PRD performance of the system is related to the severity of disease. For the coding rate of $\rho = 0.08$, the individual PRD performances of the ECG records vary from 5.11% to 7.31% depending on the characteristics of normal and pathological ECG signals. Although the 2-D compression method shows good results for normal ECG signals, it may suffer from irregular rhythms mainly due to the QRS detection stage. In order to exploit the inter-beat correlation, the ECG signal is QRS detected and then segmented according to the detected fiducial points. As a consequence, the performance of 2-D ECG compression algorithms is affected by the accuracy of the QRS detection scheme. Compared with normal subjects, the worse performance of diseased subjects may be attributed to the fact that the number of QRS false detections may increase significantly in the presence of noise and varying QRS morphology.

The next step is to evaluate the recognition performance of the proposed ECG biometric system on different datasets. The system performance is evaluated in terms of the recognition rate, which is normally defined as the ratio of the number of correctly identified subjects to the total number of testing subjects. First of all, the proposed biometric systems were individually tested on datasets from D1 to D4. Table II presents the recognition rate performances associated with various datasets for the case where the ECG images are subjected to JPEG2000

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TABLE I
AVERAGE CR AND PRD PERFORMANCES FOR JPEG2000 WITH RATE $\rho = 0.15$ AND $\rho = 0.08$.

Rate ρ		D1	D2	D3	D4
0.15	CR	14.28	9.88	10.72	10.64
	PRD	3.08%	3.54%	3.32%	3.10%
0.08	CR	21.66	17.36	19.70	19.20
	PRD	5.11%	7.31%	7.24%	7.25%

TABLE II
RECOGNITION RATES (%) OF THE PROPOSED METHODS.

Dataset	JPEG2000 ($\rho = 0.15$)		JPEG2000 ($\rho = 0.08$)	
	PA1	PA2	PA1	PA2
D1	96.18	99.98	95.45	99.99
D2	87.66	91.95	87.73	91.53
D3	91.48	95.50	91.54	95.46
D4	84.87	91.85	83.95	92.18
D1, D2	90.19	94.97	90.25	94.20
D1, D2, D3	89.98	96.39	89.16	95.92
D1, D2, D3, D4	89.55	95.72	89.39	95.66

encoding with coding rate $\rho = 0.15$ and $\rho = 0.08$. Data in the table have been averaged over 1000 trials per subject. For each subject, we randomly selected four compressed ECG images for feature extraction and one BIV results for each ECG image. Among them, the first two BIVs of each subject are used for training in the enrollment stage, and the other two BIVs are used for testing in the recognition stage. The results clearly demonstrate the improved performance achievable using PA2 in comparison to that of PA1. By the method PA2 with $\rho = 0.15$ applied individually on datasets from D1 to D4, the recognition rate was 99.98% for normal subjects, 91.95% for arrhythmia subjects, 95.50% for supraventricular arrhythmia subjects, and 91.85% for sudden cardiac death subjects. To elaborate further, we also investigate the performance of PA2 when normal and diseased subjects are jointly enrolled and tested. With this in mind, the initial 10 normal subjects are combined with an additional 10, 20, and 30 diseased subjects and the system is retrained and tested again. The results in Table II show a correct recognition rate of 94.97% when the system PA2 is jointly tested on datasets D1 and D2. When 10 other subjects from dataset D3 were added into the database, recognition rate was 96.39%. Lastly, 95.72% was achieved with the entire database containing 10 normal subjects and 30 diseased subjects. As the table shows, the additional inclusion of 30 diseased subjects only dropped the recognition rate by 4.26%. This clearly demonstrates that the proposed system PA2 is robust enough to handle the inclusion of diseased ECG in the biometric database.

VI. CONCLUSIONS

This paper proposed a fast method of ECG biometric recognition that directly uses the compressed ECG data in JPEG2000 format. Under the JPEG2000 framework, the person identification problem is analogous to a context-based image retrieval problem. In this work, we have compared the performances of two feature sets for texture characterization in compressed ECG images. The first feature set uses the energies of all subbands, whereas the second feature set is obtained by applying PCA on the wavelet coefficients of the lowest frequency subband. Also, we look into the effects of diseased subjects on the recognition rate of a compressed-domain ECG biometric system. The proposed ECG biometric system has been tested on standard ECG databases and high recognition accuracy is achieved with a low feature dimension.

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