Unsupervised Shot Boundary Detection for Temporal Segmentation of Long Capsule Endoscopy Videos

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Abstract — Physicians use Capsule Endoscopy (CE) as a non-invasive and non-surgical procedure to examine the entire gastrointestinal (GI) tract for diseases and abnormalities. A single CE examination could last between 8 to 11 hours generating up to 80,000 frames which is compiled as a video. Physicians have to review and analyze the entire video to identify abnormalities or diseases before making diagnosis. This review task can be very tedious, time consuming and prone to error. While only as little as a single frame may capture useful content that is relevant to the physicians’ final diagnosis, frames covering the small bowel region alone could be as much as 50,000. To minimize physicians’ review time and effort, this paper proposes a novel unsupervised and computationally efficient temporal segmentation method to automatically partition long CE videos into a homogeneous and identifiable video segments. However, the search for temporal boundaries in a long video using high dimensional frame-feature matrix is computationally prohibitive and impracticable for real clinical application. Therefore, leveraging both spatial and temporal information in the video, we first extracted high level frame features using a pretrained CNN model and then projected the high-dimensional frame-feature matrix to lower 1-dimensional embedding. Using this 1-dimensional sequence embedding, we applied the Pruned Exact Linear Time (PELT) algorithm to searched for temporal boundaries that indicates the transition points from normal to abnormal frames and vice-versa. The key novelty of this work is in three (3) folds - first, the automated detection of temporal boundaries in long CE video has not been previously considered. Secondly, the reduction in the computational cost of the temporal boundary detection search by using a lower dimensional frame feature embedding; and lastly, the entire temporal segmentation of the CE videos requiring no supervision from medical expert is a new concept. The output of our model can be easily integrated into any CE video summarization model where physicians only need to review a selected sample frame from each video segment. We experimented with multiple real patients’ CE videos and our result showed PCA was superior in capturing the transition between pair of normal and abnormal frames in the video. We also bench-marked with expert provided label, and our system achieved an AUC of 66% on multiple test videos.

Index Terms—Capsule Endoscopy Video, Video Temporal Segmentation, Shot Boundary Detection, Change Point Detection, Video Summarization.

I. INTRODUCTION

With an estimated 70 million Americans affected by different digestive tract diseases each year, physicians use endoscopy as the non-surgical procedure to visualize and examine the stomach, upper small bowel and colon of a person [1]. Using an endoscope, a flexible tube which carries light by fibreoptic bundles with attached camera, the physician is able to view pictures of the digestive tract on a color TV monitor. Traditionally, three main endoscopy procedures include gastroscopy, small-bowel endoscopy and colonoscopy. During gastroscopy, also known as the upper endoscopy, an endoscope is easily passed through the mouth and throat and into the esophagus, thereby allowing the physician to view the esophagus and stomach [2]. The small bowel endoscopy advances further and allows visibility into the upper part of the small intestine. Colonoscopy involves passing endoscopes into the colon through the rectum to examine the colon. Small bowel endoscopy is especially limited by how far it can advance into the small bowel, thereby limiting the extent of the physicians’ examination. All three traditional methods are also limited due to the invasiveness and discomfort that accompanies them. While there has not been a complete replacement for these traditional procedures, especially when a biopsy (removal of tissue) is necessary, Video Capsule Endoscopy (VCE) has innovatively made the endoscopy procedure a lot less invasive and less uncomfortable.

VCE is currently the standard procedure to examine the entire digestive tract without the invasiveness associated with the traditional gastroscopy, small-bowel endoscopy and colonoscopy procedures. While VCE helps ease diagnosis of many digestive tract diseases, a single capsule endoscopy study can last between 8 - 11 hours generating up to 80,000 images of various sections of the digestive tract. In a typical VCE study, up to 50,000 images are obtained for the small bowel region alone, however, it is possible for pathology of interest to be present in as few as one single frame. Notwithstanding, physicians have to review the entire video in order to identify frames capturing diseases or abnormalities.
Research efforts on automating analysis of VCE videos have been on for more than two decades and many promising methods and techniques have been developed in literature (See section II). However, many of the proposed techniques focus on identifying specific abnormalities in individual frame independent of other frames in the video. Secondly, Deep Convolutional Neural Network (DCNN) models [3] are currently state-of-the-art models in medical image analysis [4]–[6] and object recognition including various abnormality detection in VCE video frames [7]. However, despite their impressive performance on VCE video data, the variety of possible abnormalities in the gastrointestinal (GI) tract coupled with the wide inter-patient variation as well as the sample inefficiency of DCNN models limits their direct applicability towards developing a fully automated system to review and analyze CE videos.

Secondly, the capsule camera used in CE is propelled down the GI tract through peristaltic movement of the intestinal walls and the output videos have unique properties that tend to degenerate the performance of any generic video analysis technique, leading to high misses in diagnosing diseases. For example, poor illumination, food particles causing occlusion and also unstable peristaltic movement of the GI walls results in frequent camera flip sometimes leading to poor quality video output.

Lastly, many open dataset used in traditional video analysis research have already been manually segmented into short video clips with fixed frame counts of fixed time duration [8], [9]. Therefore many video analysis techniques, especially deep learning based models [10], [11], are designed to operate mostly on short video clips. Manually segmenting long video into clips have two (2) main problems: 1) The sequence of frames contained in each video clip cannot be guaranteed to be uncorrelated. Manually segmenting long videos, therefore, will not yield a homogeneous and identifiable segment that can lead to optimal summarization output; 2) When a non-homogeneous video segment is to be summarized, there is a chance of selecting a non-key frame as the representative frame, leading to higher miss-rate in any diagnosis.

II. RELATED WORK

A. VCE Video Analysis

Analysing CE videos encompasses disease or abnormality detection, quantifying severity of identified diseases, localizing identified abnormalities, and decision making on appropriate intervention by the physician. For more than two decades, researchers have proposed different techniques to automate some of these steps by leveraging both classical image analysis and machine learning techniques [12] as well as more recent and advanced deep learning based methods [13]–[16]. Prior works on VCE fall into three broad categories: 1) detect specific lesion such as bleeding in [17], polyp [18], ulcer [19], and angioectasia [20], [21]; 2) abnormal or outlier frame detection where frames with abnormalities are considered outliers [7], [22]; and 3) VCE video summarization where representative frames are selected from the entire video [15], [23]–[27] for review by the experts.

B. Video Temporal Segmentation

Temporal segmentation is usually the first step when trying to automate analysis of long videos. The goal is to divide the video stream into a set of meaningful segments or shots. Each member frame within a segment are correlated and have visual similarity while each segment will exhibit independence characteristic. Vu et al. proposed a coherent three-stage procedure to detect intestinal contractions in [28]. The authors utilized changes in intestinal edge structure of the intestinal folds for contraction assessment. The output is contraction-based shots. Mackiewicz et al. in [29] utilized three dimension LBP operator, color histogram, and motion vector to classify every 10th image of the video. The final classification result was assessed using a 4-state hidden Markov model for topographical segmentation. In [30], two color vectors that were created with hue and saturation components of HSI model were used to represent the entire video. Spectrum analysis was applied to detect sudden changes in the peristalsis pattern. The authors assumed that each organ has a different peristalsis pattern and hence, any change in the pattern may suggest an event in which a gastroenterologist may be interested. Energy and High Frequency Content (HFC) functions are subsequently used to identify such change while two other specialized features aim to enhance the detection of duodenum and cecum. Zhao et al. [22] proposed a temporal segmentation approach based on adaptive non-parametric key-point detection model using multi-feature extraction and fusion. The aim of their work was not only to detect key abnormal frames using pairwise distance, but also to augment gastroenterologist’s performance by minimizing the miss-rate and thus, improving detection accuracy. None of these prior works considered the computation cost of the temporal segmentation task and given the complexity of CE videos, the time it takes to run a model may render the solution impractical. The work presented in this paper is motivated by this challenge. In another work aimed at summarizing VCE, [15] proposed to find transition boundaries in the video using pair-wise similarity between the sequence of frames. A threshold parameter is used to determine the boundaries based on the similarity score between frame pairs. Computing pairwise similarity between video frames can be computationally prohibitive and impracticable in real world clinical setting.

C. Boundary Detection

Detection of boundaries or transition points (TP) on sequence data [31] has been considered in solving many sequence segmentation problems across various applications such as medical condition monitoring [32], climate change detection [33], audio activity segmentation and boundary recognition for silence in speech [34], speaker segmentation, scene change detection, and human activity analysis [35]. Other areas where detection and localization of distributional changes in sequence data arises include online sequential
time series analysis [36], [37]. Essentially, Change Point Detection (CPD) involves partitioning a sequence into several homogeneous temporal segments.

Techniques such as probabilistic sequence models including Hidden Markov Models (HMM) [38] or the discriminative counterpart such as Conditional Random Fields [39] are well validated. These probabilistic models require a good knowledge of the transition structure between the segments and also require careful pre-training to yield a competitive performance. This may not be practicable for online applications where data are acquired online [31], [40]. Parametric approaches model the distribution before and after the change based on maximum likelihood framework [41] while non-parametric methods [42] have been mostly limited to uni-variate data. Kernel-based methods [43] use maximum kernel fisher discriminant ratio as a measure of homogeneity between segments and can achieve good results for moderately multidimensional data or in specific situations where the data lie in a low-dimensional manifold. The approach involves a regularized kernel-based test statistic to determine if: 1) there is a change point in the data and thereafter, the location/instant of the change point. However, the method lacks robustness when moving to larger dimensions. Particularly, kernel-based methods are not robust with respect to the presence of contaminating noise and to the fact that the changes in the detected points may only affect a subset of the components of the high-dimensional data.

Algorithms such as Binary Segmentation (BS) and dynamic programming [44], [45], can identify locations where there are significant changes in the distribution of a sequence of data through recursive search. However, in order to use these techniques, prior knowledge of the number of change point instances in the sequence is required. The algorithms only try to recursively find the location of these points using maximum likelihood estimation. Also, BS search is the most established in literature. The algorithm is an approximate method with an efficient computational cost of $O(n\log n)$, where $n$ is the number of data points. Dynamic Programming (DP) search is an exact search method, with a computational cost of $O(Q^2n)$, where $Q$ is the max number of change points and $n$ is the number of data points [44]. DP can also be applied using different kernels such as the linear or Gaussian kernels. Window-Based Search is an approximate search method that computes the discrepancy between two adjacent windows that move along with signal $y$. When the two windows are highly dissimilar, a high discrepancy between the two values occurs, which is indicative of a change point. Upon generating a discrepancy curve, the algorithm locates optimal change point indices in the sequence [44]. Pruned Exact Linear Time (PELT) [46] is an unsupervised CPD technique where no prior knowledge of the number of change point is necessary. Rather the model finds the optimal location as well as count of the change points in the series based on a cost function. In temporally segmenting CE videos, no prior knowledge of the number of boundaries is available. Therefore, we considered this technique as most suitable for our task. Other related methods include Segment Neighbourhood (SN) algorithm [47] and Optimal Partitioning (OP) algorithm [48].

The key to analysis of video structured data is leveraging both spatial (images) and temporal information in the data. While analysis of CE videos has been on for more than two (2) decades, little to no attention has been paid to the temporal relationship between the sequence of frames in the video. In this work, we consider both spatial and temporal structure of the video to develop a computationally efficient method to temporally segment our long VCE video with the aim of generating multiple shorter, homogeneous and identifiable video segments that are faster and easier to review and analyse. The output of our model could be applied in other domains and also integrated into long video summarization model.

D. Problem formulation

Let $f_1, ..., f_T$ be unlabelled sequence of frames in a sample CE video $V$. Our hypothesis test consist of:

**Step 1:**

$$H_0 \rightarrow P_{f_1} = ... = P_{f_k} = ... = P_{f_T}$$

$$H_A \rightarrow \exists 1 < k^* < T : P_{f_1} = ... = P_{f_k} \neq P_{f_{k+1}} = ... = P_{f_T}$$

**Step 2:** Estimate $k^*$ from the sample if $H_A$ is true

Figure 1 shows illustration of the recursive search for a boundary in the contiguous sequence of frames. Temporal segmentation algorithm:

**Algorithm 1: VCE Video Temporal Segmentation algorithm**

**Data:** VCE video with frames $1:T$;

$V = \{f_1, f_2, ..., f_T\}$

**Result:** short video segments $\{v_1, ..., v_k\}$

**begin**

for $f_i \in V$ do

  Extract Features using CNN: $X_i \leftarrow G(f_i)$

  Project each feature vector $x_i$ to 1-D embedding $\beta_i \leftarrow x_i$

  Concatenate embedding projections $\forall f \in V$;

  $\beta = \{\beta_i, ..., \beta_T\}$

Compute transition points $\{\kappa_1, ..., \kappa_m\}$

Get segments for $V$: $\{v_j\}_{j=1}^k$

**end**
computational cost of segmenting the video from \( O \) data. Projecting from \( p \)-dimensional video features reduces the sequence for the entire video appearing like a single time series frame-features into a 1-dimensional manifold space with the towards only the normal class. Thereafter, we projected the the minority classes to minimize the bias of the network the significant class imbalance in the data, we over-sampled the choice of our architecture is motivated by \cite{14}. Due to imageNet data and then fine-tune on our VCE video frames. matrix using VGG-19 \cite{3} network model pretrained on large computational cost. In our model, We extracted the frame-features dimensions, therefore, exponentially increasing the compu- time. However, video frame features are usually in higher time-series data in one dimension with linear computational. Our work leverages concept from time series change point analysis \cite{41}, \cite{43}, \cite{46} to detect multiple transition points in a sequence of video frames. CPD methods have been successfully applied on time-series data in one dimension with linear computational time. However, video frame features are usually in higher dimensions, therefore, exponentially increasing the computational cost. In our model, We extracted the frame-features matrix using VGG-19 \cite{3} network model pretrained on large imageNet data and then fine-tune on our VCE video frames. The choice of our architecture is motivated by \cite{14}. Due to the significant class imbalance in the data, we over-sampled the minority classes to minimize the bias of the network towards only the normal class. Thereafter, we projected the frame-features into a 1-dimensional manifold space with the sequence for the entire video appearing like a single time series data. Projecting from \( p \)-dimensional video features reduces the computational cost of segmenting the video from \( O(np) \) to \( O(n) \). Thereafter, we applied the Prune Exact Linear Time (PELT) algorithm proposed in \cite{46} to detect multiple transition points in the video. Our model does not require any form of annotation from medical expert. To the best of our knowledge, this is the first work to approach VCE video analysis using concept from CPD model to exploit the temporal information in the sequence of frames. We experimented with multiple embedding methods to compare performance in the segmentation task.

### B. Lower Dimensional Feature Projection

In this section, we describe our approach for embedding the extracted features to a lower 1-dimensional feature. We applied this technique to reduce the computational complexity of finding the temporal boundaries in the video sequence from to \( O(np) \) to a linear time complexity of \( O(n) \). We approached this by projecting the high dimensional frame feature vector to a lower 1-dimensional embedding space. First, we experimented with detecting change boundaries using the high dimensional feature matrix of the video, however, after running for several days on a single video, we recognized the impracticability for real clinical application. Representing abnormalities captured in a VCE image by a single 1-dimensional feature vector is not a trivial task. Therefore, we experimented with other embedding methods to compare performance. Specifically, we experimented with PCA for linear projection and auto-encoder, TSNE, Kernel-PCA with different kernels to account for some non-linearities. We restricted our test to these techniques based on consideration for computational cost and also after experimenting with many manifold learning techniques. We briefly describe each of these embedding techniques below:

1) **Principal Component Embedding (PCE):** The principal component of a feature matrix extracts the dominant patterns in the matrix in terms of a complementary set of score and loading plots \cite{49}. PCA is a linear dimensionality reduction that is used to decompose a multivariate dataset in a set of successive orthogonal components that captures maximum variance in the data. The input data is centered but not scaled for each feature before applying Singular Value Decomposition (SVD). The computational efficiency and speed of PC method makes it a very popular option in the machine learning research community. See figure 3 for the visualization of a sample video projected on the 1-dimension that explains most variance using 4096-dimensional feature vector extracted from VGG-19.

2) **Kernel Principal Component Embedding (KPC):** In order to capture some non-linearities in the embedding, we applied kernel principal component which achieves non-linear dimensionality reduction through the use of kernels. While PCA uses a linear kernel \( k(x, y) = x^T y \) to construct the eigen-decomposition of the covariance matrix of the data, kernel-PCA uses the kernel trick by mapping the data to a hyperplane with the original linear eigen-decomposition performed in a reproducing kernel hilbert space. We experimented with two (2) different kernels - gaussian and cosine kernels. Figure 3b and 3c shows the 1-d projection using the two kernels.

Figures 3 shows the visualization of a sample video after projecting to a 1-dimensional embedding space. The cosine kernel compute the using cosine distance metrics \( d(x, y) = \frac{x^T y}{||x|| ||y||} \). Two objects that are exactly alike have zero distance. The gaussian kernel is an exponential function of the gamma scaled quadratic distance between any two points \( k(x, y) = \exp(-\gamma||x - y||^2) \). The aim of comparing multiple kernels as shown in figure 3 is to understand the impact on the sensitivity of the change point algorithm to the structure of the video embedding.

3) **Auto-Encoder:** Auto-encoders learns useful represen- tation without any supervision \cite{50}. The goal is to learn a mapping from high-dimensional observations to a lower-dimensional representation space such that the original observations can be reconstructed (approximately) from the lower-
dimensional representation. It is a parametric model that is trained using an encoder-decoder neural network architecture. We applied 2-layer architecture and optimized the parameters by minimizing the mean squared loss between the actual frame features and the reconstruction. We used a learning rate of 0.001. The pretrained autoencoder was subsequently used to encode the extracted features for the test videos to a 1-dimensional representation. Though TSNE can be computationally costly, especially with high dimensional input. We mitigate this problem by first applying PCA on the full video frame features to between 50 - 100 dimension before applying TSNE on the PCA output feature matrix. Figure 3 shows the 1-d embedding plot for our test video.

C. Shot Boundary Detection (SBD) in CE Video

In temporally segmenting CE video, we consider temporal boundary as points where there is an occurrence of a pathology between a pair of frames in the sequence. In this paper, we employed the PELT algorithm since it requires no supervision in detecting the transition points in the video. The algorithm is derived from the Optimal Programming algorithm but involves a pruning step within the dynamic program to minimize the computational cost. The pruning reduces the computational cost without affecting the exactness of the resulting segmentation making it an ideal candidate for high dimensional video data. The PELT algorithm is able to detect multiple transition points and generally produces quick and consistent results. It solves the penalized detection problem when the number of transition points in the sequence is unknown. By minimizing the log-likelihood cost function in 1, it estimates both the number of transition points as well as location of the change in a sequence of data. The algorithm has a computational cost of $O(n)$, where $n$ is the number of data points. In our case, $n$ is the number of frames in the video. The PELT algorithm can solve the change point detection problem using different kernels but the most validated is the Gaussian kernel.

On an ordered sequence of frames features $x_1, ..., x_T$, our SBD model will have $m$ transition points with their positions $\kappa_1, ..., \kappa_m$; where $1 \leq m \leq T - 1$. We specify $\kappa_0 = 0$ and $\kappa_{m+1} = T$ and assume transition points are ordered such that $\kappa_i < \kappa_j$. The $m$ transition points will split the data into $m + 1$ segments with the $i^{th}$ segment containing $x_{(\kappa_{i-1}+1):\kappa_i}$

The algorithm begins by first conditioning on the last point of change, it then iteratively relates the optimal value of the cost function to the cost for the optimal partition of the data prior to the last transition point plus the cost for the segment for the last point to the end of the data [46]. We set $\kappa = \{k : 0 = \kappa_0 < \kappa_1 < \cdots < \kappa_m < \kappa_{m+1} = T\}$ as the set of possible vectors of transition points for the video. Set $F(0) = -\beta$. The optimal partition is defined as:

$$F(s) = \min_{\kappa \in \kappa} \sum_{x=1}^{m+1} [C(x_{(\kappa_{i-1}+1):\kappa_i}) + \beta]$$

$$= \min_{\kappa \in \kappa} \left\{ \sum_{x=1}^{m} [C(x_{(\kappa_{i-1}+1):\kappa_i}) + \beta] + C(x_{\kappa_i+1}:n) + \beta \right\}$$

$$= \min_{\kappa \in \kappa} \left\{ F(t) + C(x_{\kappa_i+1}:n) + \beta \right\}$$

(1)

Where $C$ is a cost function for the $i^{th}$ segment; $\beta_m$ is a regularizer to guard against over fitting which essentially determines how many transition points the algorithm will find. The higher the specified $\beta_m$ the less the number of detect transition points forcing the algorithm to minimize the False Positives Rate (FPR). It is important to experiment with this
TABLE I: Small Bowel Frame Count for Train and Test videos

| Video ID | Training samples | Testing samples |
|----------|------------------|-----------------|
| Video 1  | 12,303           | -               |
| Video 2  | 13,177           | -               |
| Video 3  | 8,452            | -               |
| Video 4  | 23,124           | -               |
| Video 5  | 32,181           | -               |
| Video 6  | -                | 8,701           |
| Video 7  | -                | 16,909          |
| Video 8  | -                | 10,037          |

hyper-parameter to make sure increasing the penalty $\beta_{m}$ is not jeopardising the ability to detect true transition points or true positives (TP).

$$C(x(\kappa_{i-1}+1):\kappa_{i}) =$$

$$C = \left(\kappa_{i} - \kappa_{i-1}\right) \left(\log(2\pi) + \log\left(\frac{1}{\kappa_{i} - \kappa_{i-1}}\right) + 1\right) + \left(\sum_{i=1}^{\kappa_{i}}(x_{i} - \mu)^{2}\right)$$

$C$ is chosen as twice the negative log-likelihood as in eq. 2 and the minimum segment length $\kappa_{i-1} - \kappa_{i} \geq 1$.

IV. EXPERIMENTS

We conducted experiments using eight (8) VCE videos collected during real clinical examination under the supervision of expert gastroenterology. During review and analysis of CE videos, gastroenterologist are mostly interested in the small bowel region which can only be accessed through VCE and not through any of the other upper or lower endoscopy procedures. Detecting pathological change within the small bowel is a much more difficult problem that detecting transition between regions of the GI tract such as esophagus, stomach and colon.

For our experiment, we therefore trim the long video to focus only on the small bowel region. Table I shows the number of frames in the videos. We extracted the videos from the RapidReader software program and pre-processed each video into frames. The eight (8) videos were collected from different patients during a clinical endoscopy procedure using the SB3 Given Imaging PillCam capsules.

We randomly selected 5 videos for pre-training our feature extraction model and also to perform pre-training of the autoencoder. We reserved the remaining three (3) videos for testing the entire system. Using videos from completely different patients during testing helps minimize any bias and ensures our approach will generalize to any new unseen patient video data.

A. Implementation

We developed our entire system using the Pytorch framework on NVIDIA GTX2080 machine. We ensured that all our experiment were run on the same configuration for consistency across the compared techniques. Each of the feature extractors were trained for up to 30 epochs using 0.001 as learning rate and Stochastic Gradient Descent optimization. We also trained the autoencoder to embed the frame-features for about 50 epochs. During each of the pre-training, we over-sampled the minority classes based on the inverse of their proportion in the data. This gave a significant boost to the representation capability of the network on the abnormal frames.

B. Evaluation

We evaluated the performance of this method based on the AUC-ROC as shown in table II. At each time step $t$, the model predicts whether $t$ is a transition point or not. A transition point is defined when the class of frame at $t-1$ is different from the class of frame at $t$. Using the predicted output, we computed the True Positive and False Positive rates and we applied this in computing the ROC. Each transition point is considered to be a pathological event and so we bench-marked against the ground truth label provided by the medical experts. This is, obviously a very challenging problem as both the change point detection algorithm and the feature-embedding models do not have any information on the statistical property that characterizes any of the pathologies in the video.

V. RESULTS AND DISCUSSION

Figure 4 shows experimental results of detected boundaries using PCA embedding and the PELT change point algorithm. Each of the alternating pink-colored intervals are sections of some pathological abnormality. There are points where visually we can observe changes but are not pathological events. These points are due to the camera rotation and flips as it is propelled down the GI tract through peristalsis. This means there is a spatial transition in the content captured by the camera but those changes are not pathological changes.

Experiments on feature extraction also showed that feature extraction capability of the base CNN model is critical to what the boundary detector is able to identify. The representation capability of the base CNN of the diseased-frames will impact the performance of the boundary-detection algorithm. In addition, different CNN architectures showed varying representation performance when applied on different classes of diseases (or lesions). This means, for example Resnet-152...
may better represent diffuse bleeding in a frame than VGG-19. Lesions show significant difference both geometrically and in terms of color, texture as well as the surrounding lighting condition. This indicates that the base CNN capabilities are not universal and some architectures better capture some structure than others.

Table II below shows comparative results using different parametric and non-parametric embedding techniques. Parametric representation frameworks such as auto-encoder are very difficult to train, but are able to capture some non-linearities in the data wherever they successfully train.

Table II compares the receiver operating characteristics of different embedding techniques with the TPR and FPR aggregated over the test videos. From the table II, while some embedding performed worse than random encoding, PCA with linear kernel achieved an AUC of 0.66, outperforming other embedding techniques. Clearly, PCA is able to better encode the frame features to capture more abnormal boundaries than other embedding techniques including the autoencoder (0.42) and TSNE (0.49).

While VGG-19 was able to encode the frames and separate diseased frames from the normal frames, the final pool layer of the model has 4096 features. Embedding this to 1-dimensional vector is not a trivial problem due to the complexity of the CE video frames features and the complex geometry of some abnormalities, such as angioectasia, that may be difficult to detect, even by humans.

1) Detected Video Boundaries in a Sample Test Video: Figure 5 below show the detected transition points in the sequence of frames.

As shown in figure 5, some of the boundaries detected in the sequence of video frames are not necessarily indicative of pathological change event. However, very similar frames are captured in the same temporal boundaries. Clearly, detecting pathological boundaries in VCE videos is not trivial and also a very challenging problem. Therefore, a binary classification model that can encode the abnormalities into binary category may help mitigate this challenge.

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