IBM Research TREC-2002 Video Retrieval System

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Abstract

In this paper, we describe the IBM Research system for analysis, indexing, and retrieval of video, which was applied to the TREC-2002 video retrieval benchmark. The system explores methods for fully-automatic content analysis, shot boundary detection, multi-modal feature extraction, statistical modeling for semantic concept detection, and speech recognition and indexing. The system supports querying based on automatically extracted features, models, and speech information. Additional interactive methods for querying include multiple-example and relevance feedback searching, cluster, concept, and storyboard browsing, and iterative fusion based on user-selected aggregation and combination functions. The system was applied to all four of the tasks of the video retrieval benchmark including shot boundary detection, concept detection, concept exchange, and search. In this paper, we describe the approaches for each of the tasks and discuss some of the results.

1 Introduction

The growing amount of digital video is driving the need for more effective methods for indexing, searching, and retrieving video based on its content. Recent advances in content analysis, feature extraction, and classification are improving capabilities for effectively searching and filtering digital video content. Furthermore, the recent MPEG-7 standard promises to enable interoperable content-based retrieval by providing a rich set of standardized tools for describing features of multimedia content [SS01]. However, the extraction and use of MPEG-7 descriptions and the creation of usable fully-automatic video indexing and retrieval systems remains a significant research challenge.

The TREC video retrieval benchmark is allowing advances in the area of content-based retrieval by fixing a video corpus and different query and detection tasks. This allows experimentation with new video indexing techniques, with consistent measures for assessing progress. This year, we participated in the TREC video retrieval benchmark and submitted results for four tasks: (1) shot boundary detection, (2) concept detection, (3) concept exchange, (4) search. We explored several diverse methods for video analysis, indexing, and retrieval, which included automatic descriptor extraction, statistical modeling, and multi-modal fusion. We conducted experiments that individually explored audio-visual and speech modalities as well as their combination in manual and interactive querying. In the paper, we describe the video indexing and retrieval system and discuss the results on the video retrieval benchmark.

1.1 Outline

In this paper, we describe the video indexing and retrieval system and examine the approaches and results on the TREC-2002 video retrieval benchmark. The outline is as follows: in Section 2, we describe the process for video indexing including video content indexing and speech indexing. In Section 3, we describe the video retrieval system including methods for content-based search, model-based search, speech-based search, and other methods for interactive searching and browsing. In Section 4, we discuss the approaches for each of the benchmark tasks and examine some of the results.

2 Video indexing system

The video indexing system analyzes the video in an off-line process that involves video content indexing and speech indexing. The video content indexing process consists of shot boundary detection, key-frame extraction, feature extraction, region extraction, concept detection, and clustering, as shown in Figure 1. The basic unit of indexing and retrieval is a video shot.
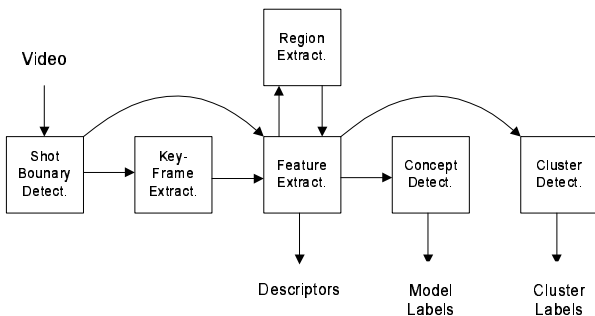
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Figure 1: Summary of video content indexing process.

2.1 Shot boundary detection (SBD)

The shot boundary detection (SBD) is performed using the real-time *IBM CueVideo* system [Cue] which automatically detects shots and extracts key-frames. This year, we explored several methods for making SBD more robust to poor video quality. Some of the methods include using localized edge gradient histograms and comparing pairs of frames at greater temporal distances. Overall, the 2002 system showed reduction in SBD errors by more than 30% compared to the 2001 SBD system [SSA+02].

The baseline CueVideo SBD system uses sampled, three-dimensional color histograms in RGB color space to compare pairs of frames. Histograms of recent frames are stored in a buffer to allow a comparison between multiple image pairs up to seven frames apart. Statistics of frame differences are computed in a moving window around the processed frame and are used to compute the adaptive thresholds, shown in Figure 2 as a line above the difference measures (Diff1, Diff3 and Edge1). A state machine is used to detect the different events (states). The SBD system does not require any sensitivity-tuning parameters. More details about the baseline system can be found in [SPA+99, SSA+02].

Several changes were incorporated to the baseline SBD algorithm to accommodate lower video quality, such as for the dated videos in TREC-02 data set. Localized edge-gradient histograms were added to overcome color errors. The 512-bin edge-gradient histogram counts the number of pixels in each of eight image regions, having similar I_x, I_y derivatives (each derivative is quantized into three bits). Thus it is invariant to any global light and color changes across the entire image. Rank filtering was added in time/space/histogram at various different points along the processing to handle the new types and higher levels of noise. More comparisons of pairs of frames at distances up to thirteen frames apart were added to overcome the high MPEG-1 compression noise. Several new states were added to the state machine to detect certain types of video errors and to detect very short dissolves, 2-3 frames long. These changes were evaluated using systematic precision-recall

measurements of many different variations of the system. Evaluation was carried using two data sets, one consisting of about half of the TREC01 test set with NIST ground truth data, and the other with twelve video segments, each one to two minutes long, taken from TREC02 training set for which ground truth was generated manually.
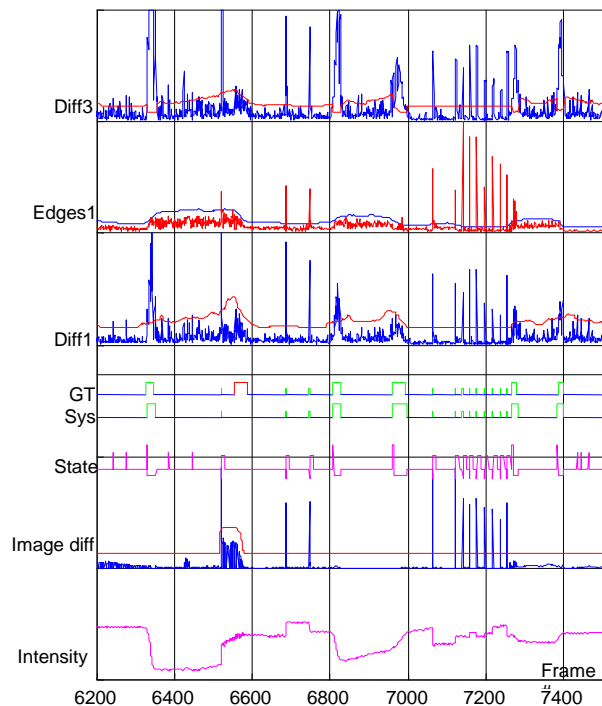

Figure 2: Plot of frame-to-frame processing of the SBD algorithm. Notice the ground truth (GT) and system output (Sys) plots for this segment of video which has six dissolves (one missed) and twelve cuts.

2.2 Feature extraction

The system extracts a number of descriptors for each video shot. Some of the descriptors as indicated below are extracted in multiple ways from each key-frame image using different normalization strategies (see [SN02]) as follows: (1) globally, (2) based on 4x4 grid, (3) based on 5-region layout, and (4) based on automatically extracted regions. The following descriptors were extracted:

- Color histogram (global per key-frame, 4x4 grid, 5-region layout, segmentation regions): one based on a 166-bin HSV color space [Smi01] and another based on 512-bin RGB color space,

- Edge orientation histogram (global per key-frame, 4x4 grid, 5-region layout): based on Sobel filtered image

and quantization to 8 angles and 8 magnitudes [SN02],

- Wavelet texture (global per key-frame, 4x4 grid, 5-region layout): based on wavelet spatial-frequency energy of 12 bands using quadrature mirror filters [Smi01],

- Color correlogram (global per key-frame, 4x4 grid, 5-region layout): based on a single-banded auto-correlogram coefficients extracted for 8 radii depths in 166-color HSV color space [HKM$^+$99],

- Co-occurrence texture (global per key-frame, 4x4 grid, 5-region layout): based on entropy, energy, contrast, and homogeneity features extracted from gray-level co-occurrence matrices at 24 orientations [JKS95],

- Motion vector histogram (global per shot, segmentation regions): based on 8×8 motion estimation blocks in the MPEG-1 decoded I and P frames. A six-bin histogram is generated based on the motion vector magnitudes,

- Visual perception texture (global per key-frame, segmentation regions): Three values representing the coarseness, contrast, and directionality, respectively [TMY78],

- Mel-Frequency Cepstral Coefficients (MFCC): transformation of uncompressed PCM signal to 24 MFCC features including the energy coefficient [RJ93].

2.3 Region extraction

In order to better extract local features and detect concepts, we developed a video region segmentation system that automatically extracts foregreound and background regions from video, as shown in Figure 3. The system runs in real-time with extraction of foreground and background regions from I-frames and P-frames in MPEG-1 video.

(a)   (b)

Figure 3: Example region segmentation results (bounding boxes of extracted regions): (a) background segmentation, (b) foreground object segmentation.

The segmentation of the background scene regions uses a block-based region growing method based on color his-

tograms, edge histograms, and directionality. The segmentation of the foreground regions uses a spiral searching technique to calculate the motion vectors of I- and P- frames. The motion features are used in region growing in the spatial domain with additional tracking constraints in the time domain. Although we tested MPEG-1 compressed-domain motion vectors, we found them to be too noisy. We also found that combining motion vectors, color, edge, and texture information for extraction of foreground objects did not give significantly better results than using only motion information.

2.4 Clustering

We used the extracted visual descriptors (see Section 2.2) to cluster the video shots into perceptually similar groups. We used a k-means clustering algorithm to generate 20 clusters. We found color correlograms to achieve an excellent balance between color and texture features. The clusters were later used to facilitate browsing and navigation for interactive retrieval (as described in Section 3.5).

2.5 Concept detection

The concept detection system uses the labeled training video content to classify unknown video content (in our case, the feature test and search test data). We have investigated several different types of static models including Support Vector Machines (SVM) and Gaussian Mixture Models (GMM).

2.5.1 Lexicon design

The first step in designing a semantic concept detection system is the construction of a concept lexicon [NBS$^+$02]. We viewed the training set video and identified the most salient frequently occurring concepts and fixed a lexicon of 106 concepts, which included the 10 concepts belonging to the TREC concept detection task (denoted as primary concepts). Overall, we generated training and validation data and modeled the 10 primary concepts as follows: Outdoors, Indoors, Cityscape, Landscape, Face, People, Text Overlay, Music, Speech and Monologue and 39 secondary generic concepts as follows:

- Objects: Person, Road, Building, Bridge, Car, Train, Transportation, Cow, Pig, Dog, Penguin, Fish, Horse, Animal, Tree, Flower, Flag, Cloud,

- Scenes: Man Made Scenes, Beach, Mountain, Greenery, Sky, Water, Household Setting, Factory Setting, Office Setting, Land, Farm, Farm House, Farm Field, Snow, Desert, Forest, Canyon,

- Events: Parade, Explosion, Picnic, Wedding.

Figure 4: VideoAnnEx MPEG-7 video annotation tool. The system enables semi-automatic annotation of video shots and editing of the lexicon.

2.5.2 Annotation

In order to generate training and validation data, we manually annotated the video content using two annotation tools[1] – one produced the visual annotations and the other produced audio annotations. The IBM MPEG-7 Video Annotation Tool (*a.k.a. VideoAnnEx*), shown in Figure 4, allows the shots in the video to be annotated using terms from an imported lexicon. The tool is compatible with MPEG-7 in that the lexicons can be imported as MPEG-7 classification schemes and generates MPEG-7 descriptions of the video based on the detected shots and annotations. The tool also allows the users to directly edit the lexicons.

IBM Multimodal Annotation Tool provides three modes of annotation: video, audio with video, or audio without video. The audio annotation is based upon audio segments in which the user manually delimits each segment within the audio upon listening and selects from the lexicon those terms that describe the audio content. Multimodal concepts (e.g. Monologues) are annotated using audio with video mode of annotation.

2.5.3 Training and validation

Training and validation of models was done using the NIST feature training data set. We randomly partitioned the NIST feature training data set into a 19 hour Feature Training (FTR) collection and a 5 hour Feature Validation (FV) collection. We used the FTR collection to construct the models and the FV collection to select parameters and evaluate the concept detection performance. The validation process was beneficial in helping to avoid overfitting to the FTR collection.

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[1]Available at http://alphaworks.ibm.com

2.5.4 Concept modeling

We followed an approach of acheiving semantic concept detection using a classification methodology (as investigated in [NKFH98, NKH02, NBS$^+$02]). The system learns the parameters of the classifiers using training data for each concept using statisical methods. We considered two approaches: one based on a decision theoretic approach and the other based on a risk minimization approach.

Decision theoretic approach In this approach, the descriptors are assumed to be independent identically distributed random variables drawn from known probability distributions with unknown deterministic parameters. For the purpose of classification, we assume that the unknown parameters are distinct under different hypotheses and can be estimated. In particular, each semantic concept is represented by a binary random variable. The two hypotheses associated with each such variable are denoted by H_i, $i \in \{0, 1\}$, where 0 denotes absence and 1 denotes presence of the concept. Under each hypothesis, we assume that the descriptor values are generated by the conditional probability density function $P_i(X)$, $i \in \{0, 1\}$. The class conditional densities conditional distributions over the descriptors under the two hypotheses – concept present (H_1) and concept absent (H_0) – are assumed to be generated by distinct mixtures of diagonal Gaussians in case of static concepts. For dynamic concepts or events we assume that the class conditional densities are generated by Hidden Markov Models (HMM) [Rab89] with GMMs for the observation densities [NKFH98]. The parameters of the GMMs (mean, covariance, and mixture weights) are estimated by using the Expectation Maximization (EM) [DLR77] algorithm. A ranked list of confidence measures can then be generated using the likelihood ratio test [Poo99].

Structural risk minimization Unlike the decision theoretic approach, the discriminant approach focusses only on those characteristics of the feature set that discriminate between the two hypotheses of interest. The idea of constructing learning algorithms based on the structural risk minimization inductive principle was proposed in [Vap95]. Support vector machines (SVM) achieve discrimination by mapping the feature vectors into a higher dimensional space through nonlinear function and constructing the optimal separating hyperplane. Considering a set of patterns $\{\vec{x_1}, \ldots, \vec{x_n}\}$ with a corresponding set of labels $\{y_1, \ldots, y_n\}$ where $y \in \{-1, 1\}$. The idea is to use a nonlinear transformation $\Phi(x)$ and a kernel $K(\vec{x_i}, \vec{x_j})$, such that this kernel K can be used in place of an inner product defined on the transformed non-linear feature vectors $< \Phi(\vec{x_i}), \Phi(\vec{x_j}) >$. The optimal hyperplane for classification in the nonlinear transformed space is then computed by converting this constrained optimization problem into its
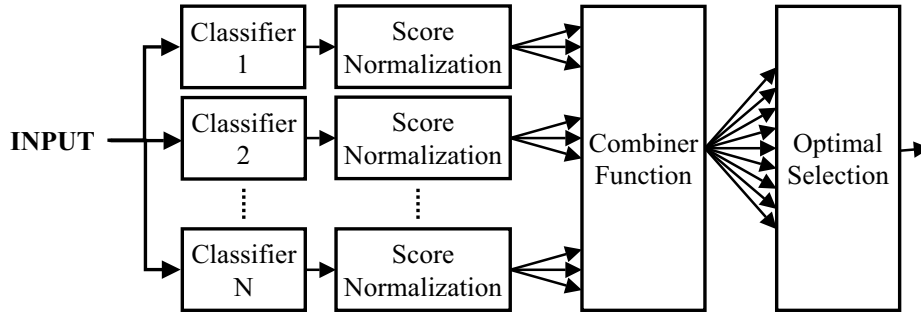
Figure 5: Three-stage normalized classifier fusion, which includes normalization of confidence socres, combination, and selection.

dual problem, using Lagrange multipliers and then solving the dual problem. If the non-linear transformation $\Phi()$ is chosen carefully, such that the kernel can be used to replace inner product in the transformed space, then the operations can be performed using the kernel in the original feature space.

2.5.5 Fusion

Since no single descriptor is powerful enough to encompass all aspects of video content and separate the concept hypotheses, fusion is needed at several levels in the concept modeling and detection processes. We experimented with two distinct approaches involving early fusion and late fusion. For early fusion we experimented with fusing descriptors prior to classification. For the late fusion we experimented with retaining soft decisions and fusing classifers. In addition, we explored various combining methods and aggregation functions for late fusion of search results as described in Section 3.6.

Feature fusion   The objective of feature fusion is to combine multiple features at an early stage to construct a single model. This approach is most suitable for concepts that have sufficiently large number of training set examples that are believed to be correlated and dependent. We experimented with feature fusion by simply concatenating descriptors. Different combinations of descriptors were used to construct models. We used the validation set to choose the best combination.

Classifier fusion   In an ideal situation, early fusion should work for all concepts, since there is no loss of information. However, practical considerations, such as limited number of training examples, limited computational resources, and the risk of overfitting the data, necessitate an alternate strategy. If the features are fairly independent, then the loss of information is not a concern. In such situations, we use late fusion based on soft decisions that emanate from models constructed independently for individual feature types or modalities. We used a separate model (SVM or GMM) for each descriptor, which results in multiple classifications and associated confidences for each shot depending on the descriptor. While the classifiers can be combined in many ways, we explored normalized ensemble fusion to improve overall classification performance as shown in Figure 5.

The normalized ensemble fusion process consists of three major steps, as shown in FIgure 5. The first step is score normalization of resulting confidences from each classifier. The second step is the aggregation of the normalized confidence scores. The third step is the optimization over multiple score normalization and fusion functions to attain optimal performance against the validation set. In the weighted average case we considered several general weighting mechanisms, such as (1) inverse entropy, (2) inverse variance, and (3) model selection. For model selection we restricted the weights to be 0 or 1 only, essentially identifying high-performing and complementary subsets of classifiers. Subsequently, an optimal selection of the best performing normalized ensemble fusion is obtained by evaluating the performance measure against the ground truth of the validation set. During the optimization stage we favor fusion methods that generalize well in order to avoid overfitting the validation set.

2.5.6 Specialized detectors

Although we chose the generic above approaches for detection of most of the concepts, for two concepts (monologues and text overlay) we explored specialized approaches.

Monologue detection   For monologue detection, we first performed speech and face detection on each shot. Then, for shots containing speech and face, we further evaluated the synchrony between the face and speech using mutual information and used the combined score thus generated to rank all shots in the corpus. Based on experimental results

of a variety of synchrony detection techniques [NIN02], we chose a scheme that models audio and video features as locally Gaussian distributions. Given a video shot, we extracted all the video frames corresponding to it and the associated audio. The audio features were segmented into locally Gaussian segments using a model selection based segmentation scheme [CG98b]. For each such locally Gaussian audio segment, we evaluated the mutual information between every pixel in the video frames and the audio features. To get a synchrony score from such a mutual information image, we computed the ratio between the mutual information of the face region and the average mutual information across the entire image. Intuitively, the higher this score the greater the synchrony between audio and video.

Text overlay detection We explored two algorithms for extracted overlay text in video and fused the results of the classifiers to produce the final concept labeling. The first method (see [SDB98]) works by extracting and analyzing regions in a video frame. The processing stages in this system are: (1) isolating regions that may contain text characters, (2) separating each character region from its surroundings and (3) verifying the presence of text by consistency analysis across multiple text blocks. A confidence measure is computed as a function of the number of characters in text objects in the frame. The second method uses macroblock-based texture and motion energy. These features are used to generate candidate text overlay regions. For each candidate region, color layering in HSV color space is used to generate several hypothetical binary images; afterwards grouping is performed on each binary image to connect and extract character blocks using connected component analysis. Finally layout analysis is used to verify the layout of these character blocks. A text region is identified if the character blocks can be aligned to form sentences or words.

2.6 Speech recognition and indexing

As in TREC-2001, we constructed a speech-based system for video retrieval. Significant improvements were made to both the automatic speech recognition (ASR) performance and the search engine performance relative to our TREC-2001 submission.

2.6.1 Automatic speech recognition (ASR)

A series of increasingly accurate speech transcriptions for the entire corpus were produced in the period leading up to the evaluation. The first set of transcriptions were produced using an IBM real-time transcription system tuned for Broadcast News; this is the same transcription system as was used in TREC-2001 [SSA+02]. Later transcriptions were produced using an off-line, multiple pass transcription system comprising the following stages:

- Remove silent videos using the output of GMM-based speech, music and silence detectors;

- Run per-video BIC-based segmentation to divide each video into shorter segments suitable for decoding [CG98a];

- Run music detection and silence detection over all BIC segments and also automatically transcribe all BIC segments using an IBM $10\times$Real-Time Broadcast News transcription System; remove pure music and silence segments, and adjust boundaries of retained speech segments based on silence locations in the transcript;

- Supervised MLLR adaptation of speaker-independent HUB4 models to TREC-2002 data using a set of eight (word-level transcribed) videos from Feature-Train [Leg95];

- Decode BIC "speech-only" segments using interpolated trigram LM;

- Unsupervised clustering of BIC "speech-only" segments into "speaker- and environment- similar" clusters [CG98a];

- Unsupervised MLLR adaptation of TREC-2002-adapted HUB4 models to each cluster using single global MLLR mean and precision transforms [Leg95].

The word error rate (WER) of the final transcripts is estimated at 38.7% on a held out set of eight videos from Search Test and Feature Test which were manually transcribed[2]. This compares favorably to 42.7% for the best of the publically-released transcriptions on the same set and represents a 41% improvement over the transcriptions used as the basis for IBM's TREC-2001 SDR system.

2.6.2 Speech indexing

Indexes were constructed for SDR from the final most accurate speech transcriptions. Three types of indexes were generated: document-based indexes, an inverse word index, and a phonetic index. No attempt was made to index the set of silent videos.

Document-level indexes: the document-level indexes support retrieval at the document level, where a document is defined to span a temporal segment containing at most 100 words[3]. Consecutive documents overlap by 50 words

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[2]Note this set does not overlap with the set used in supervised acoustic model adaptation.

[3]Minor differences in document definition were used in constructing the different indexes, such as whether or not documents boundaries are defined at long stretches of silence or music; experiments suggest these differences do not make a significant contribution to the differences in MAP across systems.

in order to address boundary truncation effects. Once documents are defined and their associated time boundaries are recorded, the documents are preprocessed using (1) tokenization to detect sentence/phrase boundaries; (2) (noisy) part-of-speech tagging such as noun phrase, plural noun etc; (2) morphological analysis, which uses the part-of-speech tag and a morph dictionary to reduce each word to its morph eg. verbs `[lands]`, `[landing]` and `[land]` reduce to `/land/`; (4) "stop" words are removed using standard stop-word lists. After pre-processing, indexes are constructed and statistics (such as word and word pair term- and inverse-document frequencies) are recorded for use during retrieval.

Inverse word index: the inverse word index supports Boolean search by providing the $(video_i, time_i)$ of all the occurrences of a query term in the videos. Preprocessing of transcripts is similar to that above.

Phonetic index: the phonetic index supports search of out-of-vocabulary words. The (imperfect) speech transcript is converted to a string of phones [AES01]. The phonetic index can be searched for sound-like phone sequences, corresponding to out-of-vocabulary query terms such as some acronyms, names of people, places, and so forth[4]

3 Video retrieval system

The video retrieval system provides a number of facilities for searching, which include content-based retrieval (CBR), model-based retrieval (MBR), speech-based search or spoken document retrieval (SDR) and other interactive methods.

3.1 Content-based retrieval (CBR)

Content-based retrieval (CBR) is an important technique for indexing video content. While CBR is not a robust surrogate for indexing based on semantics of image content (scenes, objects, events, and so forth), CBR has an important role in searching. For one, CBR compliments traditional querying by allowing "looks like" searches, which can be useful for pruning or re-ordering result sets based on visual appearance. Furthermore, in many cases, multi-example search and relevance feedback techniques are able to learn semantics from features through training that results from interactions with the user.

The objective of CBR is to match example query content to target video content using the extracted descriptors (see Section 2.2), as shown in Figure 6. The degree of match is determined on basis of feature similarity, which we have
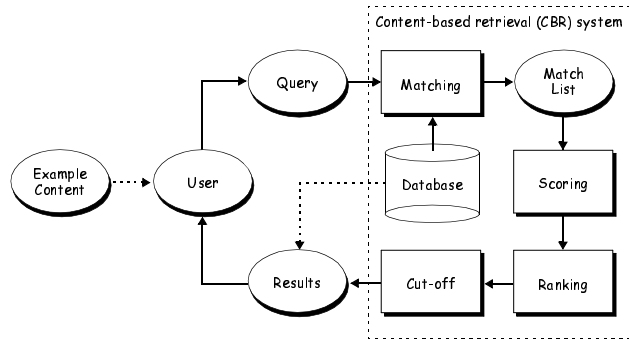

Figure 6: CBR matches example query content to target video shots and returns scored results in rank-order.

measured using Minkowski-form metrics considering values of $r = 1$ (Manhattan distance) and $r = 2$ (Euclidean distance) as follows: given descriptors represented as multi-dimensional feature vectors, $\mathbf{v}_q$ and $\mathbf{v}_t$ be the query and target vectors, respectively, then

$$d_{q,t}^r = (\sum_{m=0}^{M-1} |v_q[m] - v_t[m]|^r). \quad (1)$$

Furthermore, in the case of histogram descriptors (eg., color histograms, edge histograms – see Section 2.2), we use the following class of normalizations, where $r = 1, 2$, and $\mathbf{h}$ corresponds to an M-dimensional histogram:

$$\mathbf{v}^r = \frac{\mathbf{h}}{(\sum_{m=0}^{M-1} |h[m]|^r)^{1/r}}, \quad (2)$$

which allows the comparison of images of different sizes.

3.2 Model-based retrieval (MBR)

Model-based search allows the user to retrieve video shots based on the concept labels produced by the models (see Section 2.5). In MBR, the user enters the query by typing label text, or the user selects from the label lexicon. Since a confidence score is associated with each automatically assigned label, MBR ranks the shots using a distance $\mathcal{D}$ derived from confidence $\mathcal{C}$ using $\mathcal{D} = 1 - \mathcal{C}$.

3.3 Speech-based search (SDR)

Speech-based search allows the user to retrieve video shots based on the speech transcript associated with the shots. We used multiple SDR systems independently and combined the results to produce the final SDR results for TREC-2002; we refer to the three systems as OKAPI-SYSTEM-1, OKAPI-SYSTEM-2, BOOLEAN-SYSTEM-1. To evaluate different design decisions, a limited ground truth was created for the combined FTR and FV collections by pooling the results and performing relevance assessment.

Query development and preprocessing: All SDR systems operate using a textual statement of information need. Query strings are preprocessed in a similar manner to the documents: tokenization, tagging and morphing gives the final query term sequence for use in retrieval.

Video segment retrieval: Given a query, the three SDR systems rank documents or video segments as follows:

- OKAPI-SYSTEM-1, OKAPI-SYSTEM-2: a single pass approach is used to compute a relevancy score for each document. Each document is ranked against a query, where the relevancy score is given by the Okapi formula [RWSJ$^+$95]. The total relevancy score for the query string is the combined score of each of the query terms. The scoring function takes into account the number of times each query term occurs in the document and how rare that query term is across the entire corpus, with normalization based upon the length of the document to remove the bias towards longer documents since longer documents are more likely to have more instances of any given word.

- BOOLEAN-SYSTEM-1: a Boolean search was applied to Boolean queries. This search also supported phonetic search of out-of-vocabulary words using the phonetic index, in conjunction with in-vocabulary words which can be located in the inverse word index.

Many SDR systems use the results of first pass retrieval as the basis for automatic query expansion scheme prior to running a second pass of retrieval. Experiments showed little gain from using an LCA-based scheme [XC00] on FTR+FV, since the number of relevant documents retrieved per query in the first pass is quite low, so the approach was not investigated further.

Video segment-to-shot mapping: NIST evaluate video retrieval performance at the level of shots, rather than at the level of documents or video sgments which span one or more shots. Thus we must somehow use the scores assigned to documents or video segments by SDR to assign scores at the level of shots[5]. The mappings used in the three component systems are:

- OKAPI-SYSTEM-1: the score assigned to a document is assigned to the longest shot overlapping that document;

- OKAPI-SYSTEM-2: the score assigned to a document is assigned to all the overlapping shots. A slightly higher score given to the later shots than to the first ones;

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[5]Whilst this procedure might be simplified by defining documents in a fashion more closely related to shot boundaries, our results to date have found this to be less successful than the approaches discussed above.

- BOOLEAN-SYSTEM-1: First, the boundaries of the video segment are determined by the coverage of the relevant words. Then the overlapping shots are scored the same way as with OKAPI-SYSTEM-2.

The video segment-to-shot mapping is critical to overall SDR performance. Post-evaluation experiments show the schemes above were not optimal choices; for example, since multiple relevant shots often overlap a single document, OKAPI-SYSTEM-1 performance can be improved simply by assigning a document score to all overlapping shots. Our current research is investigating more sophisticated schemes.

Fusion of multiple SDR systems: Analysis of the results from the different systems shows that they are often complementary on FTR+FV: no system consistently outperforms the others. Thus we hypothesized fusion of scores might lead to improved overall performance. Whilst various fusion schemes are possible, for TREC-2002 we use a simple additive weighted scheme to combine shot-level, zero-to-one range normalised scores from each of our basic SDR systems. Weights can be optimised on FTR+FV prior to the final run on (held-out) search test data. This combined system is termed "SDR-FUSION-SYSTEM".

3.4 Term vector search

We used term vectors constructed from the ASR text for allowing similarity search based on textual content. Given the entire collection of shots, we obtained a list of all of the distinct terms that appear in the ASR for the collection. The order of this list was fixed to give a one-to-one mapping of distinct terms and dimensions of the vector space. Each shot was then represented by an n-dimensional vector, where the value at each dimension represented the frequency of the corresponding term in each shot. This allows the comparison of two shots based on frequency of terms. We constructed several term vector representations based on ASR-text.

3.5 Browsing and navigation

The system provides several methods for browsing and navigation. For each video a story-board overview image was generated that allowed its content to be viewed at a glance. The system also generated these overview images for each cluster (see Section 2.4) and each model (see Section 2.5).

3.6 Iterative fusion

The interative fusion methods provide a way for combining and rescoring results lists through successive search operations using different combination methods and aggregation functions defined as follows:

Combination methods   Consider results list R_k for query k and results list Q_r for current user-issued search, then the combination function $R_i = \mathcal{F}_r(R_{i-1}, Q_r)$ combines the results lists by performing set operations on list membership. We explored the following combination methods:

- Intersection: retains only those shots present in both results lists.

$$R_i = R_{i-1} \cap Q_r \qquad (3)$$

- Union: retains shots present in either results list.

$$R_i = R_{i-1} \cup Q_r \qquad (4)$$

Aggregation functions   Consider scored results list R_k for query k, where $D_k(n)$ gives the score of shot with id = n and $Q_d(n)$ the scored result for each shot n in the current user-issued search, then the aggregation function rescores the shots using the function $D_i(n) = \mathcal{F}_d(D_{i-1}(n), Q_d(n))$. We explored the following aggregation functions:

- Average: takes the average of scores of prior results list and current user-search. Provides "and" semantics. This can be useful for searches such as "retrieve shots that are indoors *and* contain faces."

$$D_i(n) = \frac{1}{2}(D_{i-1}(n) + Q_d(n)) \qquad (5)$$

- Minimum: retains lowest score from prior results list and current user-issued search. Provides "or" semantics. This can be useful in searches such as "retrieve shots that are outdoors *or* have music."

$$D_i(n) = \min(D_{i-1}(n), Q_d(n)) \qquad (6)$$

- Maximim: retains highest score from prior results list and current user-issued search.

$$D_i(n) = \max(D_{i-1}(n), Q_d(n)) \qquad (7)$$

- Sum: takes the sum of scores of prior results list and current user-search. Provides "and" semantics.

$$D_i(n) = D_{i-1}(n) + Q_d(n) \qquad (8)$$

- Product: takes the product of scores of prior results list and current user-search. Provides "and" semantics and better favors those shots that have low scores compared to "average".

$$D_i(n) = D_{i-1}(n) \times Q_d(n) \qquad (9)$$

- A: retains scores from prior results list. This can be useful in conjunction with "intersection" to prune a results list, as in searches such as "retrieve shots of beach scenes but retain only those showing faces."

$$D_i(n) = D_{i-1}(n) \qquad (10)$$

- B: retains scores from current user-issued search. This can be useful in searches similar to those above but exchanges the arguments.

$$D_i(n) = Q_d(n) \qquad (11)$$

3.7   Normalization

The normalization methods provide a user with controls to manipulate the scores of a results list. Given a score $D_k(n)$ for each shot with id = n in results set k, the normalization methods produce the score $D_i(n) = \mathcal{F}_l(D_{i-1}(n))$ for each shot n as follows:

- Invert: Re-ranks the results list from bottom to top. Provides "not" semantics. This can be useful for searches such as "retrieve shots that are *not* cityscapes."

$$D_{i+1}(n) = 1 - D_i(n) \qquad (12)$$

- Studentize: Normalizes the scores around the mean and standard deviation. This can be useful before combining results lists.

$$D_{i+1}(n) = \frac{D_i(n) - \mu_i}{\sigma_i}, \qquad (13)$$

where μ_i gives the mean and σ_i the standard deviation, respectively, over the scores $D_i(n)$ for results list i.

- Range normalize: Normalizes the scores within the range $0 \ldots 1$.

$$D_{i+1}(n) = \frac{D_i(n) - \min(D_i(n))}{\max(D_i(n)) - \min(D_i(n))} \qquad (14)$$

3.8   Shot expansion

The shot expansion methods allow the user to expand a results list to include for each shot its temporally adjacent neighbors. This can be useful in growing the matched shots to include a larger context surrounding the shots, as in searches such as "retrieve shots that surround those specific shots that depict beach scenes."

3.9   Multi-example search

The multi-example search method allows the user to select multiple positive example shots from a results list and issue a query that is executed as a sequence of independent searches using each of the selected shots. The user can also select a descriptor for matching (such as those in Section 2.2) and an aggregation function for combining and rescoring the results from the multiple searches. Consider for each search k of K independent searches the scored

result $S_k(n)$ for each shot n, then the final scored result $Q_d(n)$ for each shot with id $= n$ is obtained using a choice of the following fusion functions:

- Average: Provides "and" semantics. This can be useful in searches such as "retrieve shots that are similar to shot "A" *and* shot "B".

$$Q_d(n) = \frac{1}{K} \sum_k (S_k(n)) \qquad (15)$$

- Minimum: Provides "or" semantics. This can be useful in searches such as "retrieve shots that are similar to shot "A" or shot "B".

$$Q_d(n) = \min_k (S_k(n)) \qquad (16)$$

- Maximum:

$$Q_d(n) = \max_k (S_k(n)) \qquad (17)$$

- Sum: Provides "and" semantics.

$$Q_d(n) = \sum_k (S_k(n)) \qquad (18)$$

- Product: Provides "and" semantics and better favors those shots that have low scoring matches compared to "average".

$$Q_d(n) = \prod_k (S_k(n)) \qquad (19)$$

3.10 Relevance feedback search

Relevance feedback based search techniques enhance interactive search and browsing, where user feedback on a set of shots is used to refine the search and retrieve in minimum number of iterations the desired matches. The user implicitly provides information about the matches being sought or *query concept* by marking whether shots are relevant or non-relevant in relation to his/her desired search output. The system utilizes this feedback to learn and refine an approximation to the user's *query concept* and retrieve more relevant video-clips in the next iteration.

We use a robust relevance feedback algorithm [AGG02] that utilizes non-relevant video-clips to optimally delineate the relevant region from the non-relevant one, thereby ensuring that the relevant region does not contain any non-relevant video-clips. A similarity metric estimated using the relevant video-clips is then used to rank and retrieve database video-clips in the relevant region. The partitioning of the feature space is achieved by using a piecewise linear decision surface that separates the relevant and non-relevant video-clips. Each of the hyperplanes constituting the decision surface is normal to the minimum distance vector from

a non-relevant point to the convex hull of the relevant points. With query concepts that can reasonably be captured using an ellipsoid in the feature space, the proposed algorithm gives a significant improvement in precision as compared to MARS ([RHM97]) and SVM-based relevance feedback algorithms. The relevance feedback technique is computationally robust w.r.t. the size of feedback and distribution of relevant and non-relevant video-clips. The relevant region is obtained as the result of intersection of half spaces and hence forms a convex subset of the feature space. This ensures that we can employ a quadratic distance metric to rank and retrieve video-clips inside the relevant region. Relevance feedback based search was performed using low - level color histogram and edge orientation histogram features extracted from keyframe images of video-clips.

3.11 Interface operations

The graphical user interface is shot/key-frame oriented in that the unit of query, retrieval, and display is a video shot. Figure 7 shows the key-frame display area (right-side) and the system function buttons (left-side). Some of the operations that can be conducted on each shot, such as CBR, are initiated using small buttons depicted below each key-frame image.
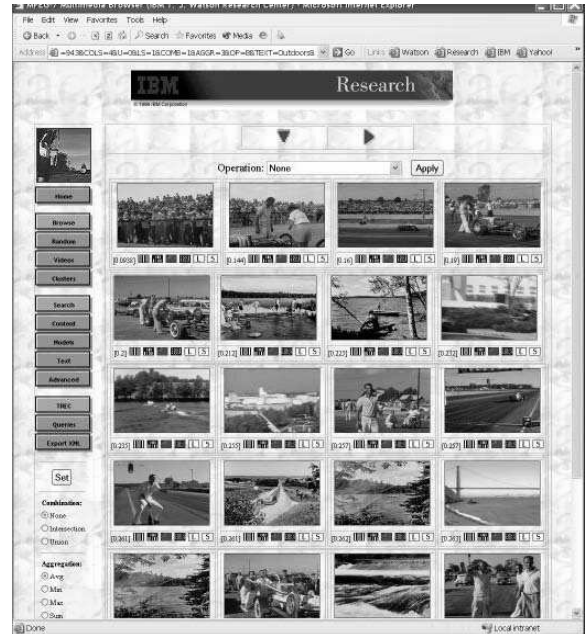

Figure 7: Screen image of the video retrieval system.

3.12 Example searches

The video retrieval system allows the CBR, MBR, SDR, and other methods of searching and browsing. The follow-

ing pedagogical queries show how the facilities of the video retrieval system can be used for querying for "beach" scenes in the case of manual, interactive, and browsing-oriented search.

Manual search Consider user looking for video shots showing a beach scene. For manual search operations the user can issue a query with the following sequence of searches, which corresponds to the following query statement (((beach color AND sky) AND water) OR beach speech):

1. Search for images with color similar to example query images of beach scenes,

2. Combine results with model = "sky" using "average" video aggregation function (Eq 6),

3. Combine with model = "water" using "product" aggregation function (Eq 9),

4. Combine with ASR test = "beach" using "minimum" aggregation function (Eq 6).

Interactive search On the other hand, for interative search operations the user can issue the following sequence of searches in which the user views the results at each stage, which corresponds to the following query statement: RFSEARCH(((EXPAND(beach speech) AND beach color) AND sky) AND water):

1. Combine with ASR text = "beach",

2. Expand results list to include adjacent shots using "expand" operation of Section 3.8,

3. Select those shots that best depict beach scenes and search for target shots with similar color and combine with previous results using "product" aggregation function (Eq 9),

4. Combine with model = "sky" using "average" aggregation function (Eq 6),

5. Combine with model = "water" using "product" aggregation function (Eq 9),

6. Select positive and negative examples of beach scenes and search for target shots using relevance feedback based on color and edges using method of Section 3.10.

For interactive searching, a more browsing oriented approach can be taken as follows:

1. Browse the video overview story boards or clusters and select the ones that best depict beach scenes,

2. Select positive and negative examples of beach scenes and search for target shots using relevance feedback.

3. Repeat.

4   Tasks and results

We participated four tasks: shot boundary detection (SBD), concept detection, concept exchange, and search.

4.1   Shot boundary detection (SBD) results

For the shot boundary detection task, the results of five systems were submitted, one of which was last year's SBD system as a baseline. A large difference in performance relative to last year was anticipated due to the degraded video quality. The other four were different versions of the improved system, mainly applying different logic to the fusion of color histogram and the localized edges histogram information. Three of them performed well and yielded very similar results, while the forth one did not perform as well. Table 1 summarizes the evaluation of the baseline system, *alm1*, and the best new system, *sys47*, on last year's and this year's TREC video data test sets. The results on TREC-01 data set were computed by us, while the results for the TREC-02 data set are taken from the official NIST TREC 2002 evaluation of those systems. Two additional rows are provided on TREC-02 benchmark that compare our results to the best and average systems, respectively, among the 54 SBD runs submitted by TREC participants.

Sys.	Video Data	All		Cuts		Gradual		Frame	
		Rc	Pr	Rc	Pr	Rc	Pr	Rc	Pr
alm1	TR-01	.95	.88	.98	.97	.87	.68	.59	.93
sys47	TR-01	.96	.92	.99	.98	.89	.79	.66	.90
alm1	TR-02	.86	.77	.93	.80	.69	.71	.48	.94
sys47	TR-02	.88	.83	.93	.87	.76	.72	.57	.89
S-5	TR-02	.84	.89	.91	.94	.76	.78	.62	.90
mean	TR-02	.76	.79	.86	.84	.53	.60	.55	.71

Table 1: Shot boundary detection results, comparing the new system with last year system on both TREC-01 and TREC-02 video data test sets. If all participating systems are to be ranked by $Pr_{All} + Rc_{All}$ then system *S-5* would be found the best one, provided here for comparison. System *mean* reflects the average of all 54 submitted systems.

As anticipated, the SBD performance on TREC-02 data was lower than on TREC-01 data set. This was very noticeable in other participating systems as well. Never-theless, the error rates of the new system *sys47* were $20 - 36\%$ lower than of the baseline system *alm1* in almost all measures on both data sets. In order to find the main causes of errors, a manual verification of all insertion errors reported by NIST evaluation was done for two of the nineteen videos

(36553.mpg and 08024.mpg). The breakdown of the sixty insertion errors is summarized in Table 2.

Cause of insertion error	freq.	%
Fast motion	12	20%
Fast zoom	5	8%
Illumination changes	4	7%
Long grad reported as two	4	7%
MPEG video error	1	2%
others	7	12%
Short/long grad missmatch	12	20%
FOI reported as two (FO+FI)	7	12%
Missing cuts in ground truth	5	8%
Fade in at video start	2	3%
Fade out at video end	1	2%
Total	60	100%

Table 2: Shot boundary detection (SBD) insertion errors - breakdown by cause.

Those errors can be divided into three group. The first group is of objective errors (56%) which are due to system fault. The second group is of subjective errors (32%) where there was a (correct, in a sense) detection of an existing boundary but it was not reported in the way defined by the evaluation criteria. For example, an FOI was reported as one FO and one FI, thus one was considered as an insertion error. Or, a long dissolve was reported as a short one and therefore was evaluated as one insertion error and one deletion error (the five frames long threshold). The last group is of ground truth errors (13%), mainly the five unlisted cuts, and some fades at the beginning or the end of videos.

4.2 Concept detection results

Overall, concept detection results were submitted for ten concept classes. The evaluation results are plotted in Figure 8, which shows shows Average Precision measured at a fixed number of documents (1000 for the feature test set). The "Average" bars correspond to the performance averaged across all participants. The "Best" bars correspond to the system returning the highest Average Precision. The "IBM" bars correspond to IBM's submitted concept detection run (priority=1). The IBM system performed relatively well on the concept detection task giving highest Average Precision on 6 of the 10 concepts[6].

Detection experiments We experimented with different kernels for non-linear projection in higher dimensional feature spaces. We used radial basis kernels as well as polynomial kernels. For each feature type or combination of

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[6]Top score is indicated only on five concepts. In our original submission to NIST, we mistakenly submitted the speech detection twice overwriting our instrument detection result. However, the actual Average Precision of our instrument sound detector was 0.686, which was reported through later communication with NIST.

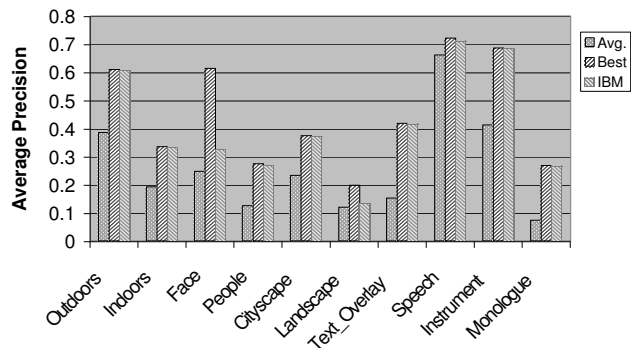**NIST TREC 2002 Concept Detection Task**

Figure 8: Comparison of concept detection performance using average precision.

feature types, we constructed independent models for each kernel (radial basis, polynomial). For each kernel we built models for different values of the parameters constrained within a reasonable range. For example, we varied the σ value of the radial basis kernel from 0.01 to 1 in different increments, evaluated the model at c values of 1, 10 and 100. We also varied the penalty for missing positive examples as against negative examples. For concepts with a small number of positive examples, we also experimented with downsizing the negative examples set for computational efficiency and to balance the ratio of positive to negative examples.

Each model was run on the validation set. The resulting list was then sorted based on the distance of each validation set example from the separating hyperplane. We thereby used the SVM classifier to rank the validation set examples such that if the example was far from the decision boundary it was assumed to have been detected with greater confidence. For each concept and each feature type/combination, we then used the validation set to choose that parametric combination which resulted in the highest non-interpolated Average Precision. Let R be the number of true relevant shots in a set of size S. Let L be the ranked list of returned shots. At any given index i let R_i be the number of relevant documents in the top i documents. Let I_j be an indicator function with $I_j = 1$ if the jth document is relevant and 0 otherwise. Assuming $R < S$, the non-interpolated Average Precision is then defined as

$$\frac{1}{R} \sum_{j=1}^{S} \frac{R_j}{j} * I_j \qquad (20)$$

We also analyzed the precision recall curve before selecting the final model.

Having selected a set of parameters for a feature type or combination, for each concept, we then performed late de-

cision fusion using normalized confidence scores. Again, the final model was selected on the basis of its validation set performance. For the auditory concepts (*speech and music* HMMs [INN02] were used to prototype the feature distributions under both hypotheses. An HMM was used to model each audio concept; each state in a given HMM has the same observation distribution, namely the GMM trained in the previous scheme. This can be viewed as imposition of a minimum duration constraint on the temporal extent of the atomic labels. Given a set of HMMs one for each audio concept we used them to generate an N-best list at each audio frame and then average these scores over the duration of the shot. We normalized these scores by dividing each concept score with the sum of all the concept scores in a particular shot. The scores are indicative of the relative strengths of the different hypotheses in a given shot rather than their absolute values.

4.3 Concept exchange results

Apart from running the primary and secondary detectors on the search test set to assist the search task, we participated in the concept exchange task by submitting results of eight primary detectors on the search test set. We generated shot based MPEG-7 descriptions for this exercise thus permitting easy exchange of the detection results between participants.

4.4 Search results

The search task required retrieving video shots from the search test collection for a given set of query topics. We investigated both manual and interactive methods of searching. We submitted four runs of all 25 query topics using the content-based, model-based, speech-based, and interactive search methods described above. Table 3 summarizes the results for the four search runs.

System	Type	Code	MAP
CBR	Manual	M_B_M_1	0.006
SDR	Manual	M_B_M-2_2	0.136
CBR+SDR	Manual	M_B_M-3_3	0.093
CBR+SDR	Interactive	I_B_M-4_4	0.244

Table 3: Summary of search results for four submitted runs.

4.5 Manual CBR

The manual CBR run consisted of mapping the query topics into one or more content-based or model-based queries and fusing the results in a predetermined fashion. As described in Section 2.2, CBR was based on a variety of descriptors. The manual CBR run was generated by allowing the following operations to answer each query topic:

1. Issue a content-based search by selecting one or more query examples, a feature type, and a fusion method, as necessary;

2. Issue a model-based search by selecting one or more concept models, a fusion method, and model weights, as necessary;

3. Fuse results lists from one or more content-based or model-based search by selecting a fusion method.

For example, the following sequence of operations was executed for Query 79: *People spending leisurely time at the beach*:

1. Pick examples 0, 1, 4, 8, 12, 23, 29 from query content set

2. Perform CBR search with edge histogram layout using "minimum" fusion (Eq 16)

3. Combine with "Landscape" model using "intersection" combining method (Eq 3) and "product" aggregation function (Eq 9).

The exact mapping of query topics into a fixed sequence of the above operations was performed manually by visually optimizing performance over the FTR and/or FV collections without knowledge of the search test collection. Once a query topic was mapped to system operations, the operations were applied to the search collection by a designated person who did not participate in the mapping process or have prior knowledge of the search test collection. Figure 9 and Figure 10 show results of manual CBR searches. Figure 9 shows the results for topic 76, which is looking for shots depicting "James Chandler." As shown, some matches are found in the results list, however, many shots of "James Chandler" are not retrieved using CBR. Figure 10 shows the results for topic 80, which is looking for shots of musicians. As shown, many of the matches correspond to musicians. This query used instrument concept detector in addition to other models.

With respect to performance, it was our experience that the TREC 2002 query topics were at a higher semantic level than what CBR can handle. While CBR and semantic modeling are generally able to capture low- to mid-level semantics, they are fairly limited in the case of only a few query examples or mid- to high-level semantics. We found that purely CBR worked best for refining candidate lists generated from semantically rich sources, such as speech, or explicit semantic models that closely match the query need. For example, refining the face model by cross-comparison with examples images of "James Chandler" did produce a few relevant hits near the top (see Figure 9). Model-based retrieval on the other hand worked well when the query topic was a close match to an existing model and was built with sufficient training data, such as the "musician" topic

Figure 9: Results for topic 76: James Chandler.

Figure 10: Results for topic 80: Musicians.

(see Figure 10). However, in the case of limited example content, such as of query topic looking for "butterflies", or given a lack of closely related explicit semantic models, CBR and MBR techniques alone are not sufficient. In addition, some of the query topics were so general (e.g., beach query) or specifiec (e.g., Price Tower query) that it is doubtful whether any reasonable discrimination can be done using low-level features alone.

4.6 Manual SDR

Manual searching using spoken document retrieval (SDR) was based on the indexed speech information. We explored multiple methods of SDR and their fusion, where the SDR queries were developed through interaction with the Feature Training collection.

Query strings were created manually for each query. Queries derived from the audio and textual statement of information need supplied by NIST were expanded by hand in ad-hoc fashion based on retrieval on the FTR+FV sets[7]. More complicated query strings are used in the Boolean system, since it was hypothesized that the Boolean retrieval would be less susceptible to the effects of query overtuning on FTR+FV.

The query terms used in the submitted multiple-SDR fusion system for topic 90 ("Find shots with one or more snow-covered mountain peaks or ridges. Some sky must be visible behind them") were "ice snow covered mountain peaks valley vista". Twenty relevant items were retrieved in the top 100, with Average Precision 0.12. For topic 84 ("Find shots of Price Tower, designed by Frank Lloyd Wright and built in Bartlesville, Oklahoma") the query terms are "Price Tower Frank Lloyd Wright Bartlesville Oklahoma", the top three items recalled are relevant and Average Precision is 0.75.

Weights for the SDR-FUSION-SYSTEM were optimised using the limited ground truth that was compiled for FTR+FV. As expected, this scheme led to Mean Average Precision (MAP) improvements FTR+FV; more importantly, fusion gave performance improvements (35%) over our best single SDR system on the unseen search test data (as shown in Table 4). Note that simple post-evaluation changes in the video segment-to-shot mapping scheme improved the performance of the individual OKAPI systems (eg. OKAPI-SYSTEM-1 increased to MAP 0.114) and the fusion system performance might be expected to improve further as the component systems improve. The results overall are a significant improvement over those for IBM's speech-only retrieval submission to TREC-2001.

System	MAP
OKAPI-SYSTEM-1	0.073
OKAPI-SYSTEM-2	0.093
BOOLEAN-SYSTEM-1	0.101
SDR-FUSION-SYSTEM	0.137

Table 4: Search test performance of component and fusion SDR systems

The OKAPI-SYSTEM-1 was used to investigate effects of increasing speech transcript accuracy, by indexing tran-

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[7]Later experients showed that, at least in OKAPI-SYSTEM-1, the gains due to the manual query expansion were negligible.

scripts of varying accuracy for the FTR+FV set for which we have compiled limited ground truth. Table 5 shows the results: a consistently increasing MAP with increasing transcript % Correct, which justifies our greater investment of effort in ASR this year. However, this result also suggests that we may not have reached an error rate at which retrieval is comparable to retrieval from ground truth transcriptions. We hope to compile a complete set of ground truth speech transcripts for the TREC-2002 videos that will allow us to answer this question.

Transcript % Correct	MAP
52.8%	0.09
59.7%	0.13
67.9%	0.17
72.8%	0.21

Table 5: Relationship between Transcript Accuracy and Retrieval Performance

4.7   Manual CBR and SDR

The combination of CBR and SDR was explored for manual searching, where queries were developed through interaction with the Feature Training collection. An example of (successful) SDR and CBR integration is query topic 86 ("find overhead views of cities - downtown and suburbs; the viewpoint should be higher than the highest building visible"). In the following, we assume that the SDR results and CBR results have been found independently prior to the integrated query:

1. Retrieve results for SDR query of "view panorama overhead downtown suburbs city town urban"

2. Expand results list to include adjacent shots (repeat two times) using expand operation (see Section 3.8)

3. Combine with CBR results using "union" combination method (Eq 4) and "product" aggregation function (Eq 9).

The final Average Precision improved from CBR 0.0 and SDR 0.039 to CBR+SDR 0.057. A similar approach was used for the other queries with minor differences such as the number of shot expansions and the choice of the combination method and aggregation function, for example, using "intersection" rather than "union" and "sum" rather than "product". However, this approach was not always successful; for example, the same scheme was used for topic 84 ("Price Tower") SDR+CBR but performance was degraded below that obtained using SDR alone. This approach to SDR and CBR integration improved four queries beyond the performance attained with SDR alone.

4.8   Interactive search

We explored interactive search using CBR and SDR in which the user interacted with the search test collection at query-time, we chose various combinations of these methods and selected among different methods for fusion, multiple examples search, relevance feedback, and browsing. The wall-clock time was measured to gauge the user effort for each interactive query. The following describes the interactive search operations for query topic 89 for "Butterflies", which took just over seven minutes of user time:

1. Search for shots of butterflies using SDR with terms such as "monarch", "butterfly", "wings", "flower".

2. View grouping of results by video (clusters shots according to source video) to get idea of which videos contribute which shots

3. Remove two unrelevant shots at top of results list

4. Expand all shots to adjacent shots

5. Results show 5 hits at the top, stop.

5   Summary

We presented the IBM Research video indexing system. The system explores fully-automatic content analysis methods for shot detection, multi-modal feature extraction, statistical modeling for semantic concept detection, and speech recognition and indexing. The system supports manual methods of querying based on automatically extracted features, models, and speech information. In this paper we described the system and the experiments runs are part of the TREC-2002 video retrieval benchmarking effort. The results show good performance on tasks such as shot boundary detection, concept detection, and search.

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