MULTI-MODAL VIDEO SUMMARIZATION USING HIDDEN MARKOV MODELS FOR CONTENT-BASED MULTIMEDIA INDEXING

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
THE MIDDLE EAST TECHNICAL UNIVERSITY

BY

YAĞIZ YAŞAROĞLU

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE
IN
THE DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

SEPTEMBER 2003

Approval of the Graduate School of Natural and Applied Sciences

____

Prof. Dr. Canan Özgen

Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

____

Prof. Dr. Mübeccel Demirekler

Head Of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

____

Assoc. Prof. Dr. A. Aydın Alatan

Supervisor

Examining Committee Members

Assoc. Prof. Dr. Tolga Çiloğlu	________________________
Assoc. Prof. Dr. Gözde Bozdağı	________________________
Assoc. Prof. Dr. Buyurman Baykal	________________________
Assoc. Prof. Dr. A. Aydın Alatan	________________________
Prof. Dr. Enis Çetin	________________________

ABSTRACT

MULTI-MODAL VIDEO SUMMARIZATION

USING HIDDEN MARKOV MODELS

FOR CONTENT-BASED MULTIMEDIA INDEXING

Yaşaroğlu, Yağız

MSc., Department of Electrical and Electronics Engineering

Supervisor: Associate Professor A. Aydın Alatan

September 2003, 75 pages

This thesis deals with scene level summarization of story-based videos. Two different approaches for story-based video summarization are investigated. The first approach probabilistically models the input video and identifies scene boundaries using the same model. The second approach models scenes and classifies scene types by evaluating likelihood values of these models. In both approaches, hidden Markov models are used as the probabilistic modeling tools. The first approach also exploits the relationship between video summarization and video production, which is briefly explained, by means of *content types*. Two content types are defined, dialog driven and action driven content, and the need to define such content types is demonstrated by simulations. Different content types use different hidden Markov models and features. The selected model segments input video as a whole. The second approach models scene types. Two types, dialog scene and action scene, are defined with different features and models. The system classifies fixed sized partitions of the video as either of the two scene types, and segments partitions separately according to their scene types. Performance of these two systems are compared against a deterministic video summarization method employing clustering based on visual properties and video structure related rules. Hidden Markov model based video summarization using content types enjoys the highest performance.

Keywords: Video summarization, hidden Markov models, content-based indexing.

ÖZ

İÇERİK TABANLI ÇOKLUORTAM ENDEKSLEMESİ İÇİN

SES VE GÖRÜNTÜ BİLGİSİ YARDIMIYLA

SAKLI MARKOV MODELİ KULLANARAK VİDEO ÖZETLEME

Yaşaroğlu, Yağız

Yüksek Lisans, Elektrik ve Elektronik Mühendisliği Bölümü

Tez Yöneticisi : Doçent Dr. A. Aydın Alatan

Eylül 2003, 75 sayfa

Bu tez çalışması öyküye dayanan videoların sahne seviyesinde özetlenmesi üzerine bir çalışmadır. Probleme iki ayrı bakış açısından yaklaşılmıştır. Birinci yaklaşım videoların bütün halinde modellenmesini öngörmektedir. Elde edilen model yardımıyla sahne sınırları belirlenmektedir. İkinci yaklaşım farklı türdeki sahneler için modeller oluşturulmasına ve videonun analizi sırasında sahne türlerinin belirlenmesine dayanmaktadır. Her iki yöntemde de kullanılan modeller saklı Markov modelleridir. Birinci yöntemde tez kapsamında kısaca değinilen video özetleme ile video prodüksiyonu arasındaki ilişkiden yararlanmak için *içerik türleri* tanımlanmıştır. Sistemde iki içerik türü gerçeklenmiş (hareket ağırlıklı içerik ve diyalog ağırlıklı içerik) ve yapılan deneylerde gereklilikleri doğrulanmıştır. Farklı içerik türleri farklı saklı Markov modelleri ve öznitelikler kullanmaktadır. İçerik türüne göre seçilen model videoyu bir bütün olarak işleyip bölütlemektedir. İkinci yöntemde ise sahne türleri modellenmektedir. Farklı modeller ve öznitelikler kullanan iki sahne türü belirlenmiştir: hareketli sahneler ve diyalog sahneleri. Girdi videonun sabit uzunluktaki parçaları iki sahne türünden birisine sınıflanır, ve her parça ayrı ayrı sahne türüne göre bölütlenir. İki yöntemin performansı görsel öselliklere ve video yapısıyla ilgili kurallara dayanan bir topaklama metoduyla karşılaştırılmıştır. Saklı Markov modelleri kullanarak içerik türüne bağlı video özetleme en iyi performansa sahiptir.

Anahtar kelimeler: Video özetleme, saklı Markov modelleri, içerik tabanlı endeksleme.

ACKNOWLEDGMENTS

I would like to acknowledge the skillful supervision and supreme vision of Assoc. Prof. Dr. Aydın Alatan, both of which were crucial to development of this thesis; and the valuable comments of examining committee members Assoc. Prof. Dr. Tolga Çiloğlu, Assoc. Prof. Dr. Gözde Bozdağı, Assoc. Prof. Dr. Buyurman Baykal and Prof. Dr. Enis Çetin.

I would like to thank my family for their unwavering support.

I would like to raise my glass to my “Brothers in Arms,” and to Cağlar, Ekin and Onur, and to my friends at EnkarE for our long lasting friendship and the bottomless well of inspiration.

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

Rate of digital content creation and duplication has increased. The Internet Movie Database reports that in their database there are 10128 movie titles produced in 2002, 93422 in the last decade [1], and that is only the movie industry. Amount of daily content created by TV channels over the world cannot be measured: On-site news shooting, in-studio programs, sports event broadcasts, in-house produced films, serials, documentaries, and other production jobs, broadcasted everyday to homes of billions. However, content creation is not in the monopoly of studios or production firms. Dyne:bolic, a single bootable CD Linux distribution, collects a wide array of open source digital content creation tools, from recording utilities to video/audio editing tools and web-broadcasting applications [2]. It enables any sufficient computer to become a studio, managed by ordinary users. All the while the Internet, with its decentralized, end-point centered architecture, enables millions of netizens to share digital content with unprecedented ease, despite all attempts to strangle it. Advanced mobile and multimedia technologies, such as web-enabled cellular phones, multimedia messaging and media streaming allow people to interact with multimedia data everywhere. Digital content is ubiquitous.

This increased generation and distribution rate of audiovisual content created a new problem: management of the content. Unlike tools to create and distribute, tools to manage multimedia content are not mature enough. Neither there is a feasible way to automatically analyze and classify content, nor browsing the content is easy. As a matter of fact, current solutions to large scale multimedia content database management are usually meta-data driven. For example, Turkish Radio and Television (TRT), having the largest video archive in Turkey, relies on unstandardized, ad hoc information about the video, entered by the producer of the video, and possibly remembered only by him. As another approach, an attempt to label all multimedia content in such a large-scale database manually, uniformly according to a standard is both infeasible and error-prone. The most widespread solution other than meta-data generation is traditional linear browsing through multimedia content. Unfortunately, this solution is too tedious.

Automatic video summarization emerges as a solution to the problem of managing video content. Automatic video summarization can be defined as identifying relevant parts of a video and presenting it in an easily browsable form, with minimal user intervention [3].

1.1 Scope of the Thesis

This thesis deals with scene level summarization of story based videos using hidden Markov models. Two different approaches to summarization are implemented: Video modeling and scene modeling. In both cases four features are extracted from the video stream for each shot in the video: Face existence, audio class, location change existence and motion activity level. In both cases the feature sequence vector is used as input to hidden Markov models. In the first case, the video modeling, hidden Markov models are used to model the videos where in the second case they model scenes. Using hidden Markov models, shot type labels are assigned to each shot by Viterbi segmentation and these type labels are used to identify scene boundaries.

Performance of both methods are investigated through simulations made against subjective ground truth data. Performance of a rule-based method is also investigated and compared to the introduced methods.

1.2 Outline of the Thesis

In the second chapter, different aspects of video summarization will be investigated. Relation of video summarization to video production, and ways to exploit this relationship is examined. Moreover, structure of a story-based video, the kind of video of primary interest to this thesis, is laid out.

In Chapter 3, hidden Markov models, which are used as the decision making mechanism in this thesis, are discussed.

In Chapter 4, the proposed video summarization system is explained in detail. This chapter is the main contribution of this thesis. Two approaches for video summarization are implemented, both using hidden Markov models (HMM). The first approach takes affects of video production into account by means of *content types* which are also defined in this chapter. It models videos with HMMs. The second approach models scenes with HMMs, and aims to identify and classify scene types for summarization.

The following chapter deals with the performed simulations. Performance of the proposed system is compared against another video summarization methods.

In the final chapter conclusive remarks and thoughts about future work are given.

CHAPTER 2

VIDEO SUMMARIZATION

2.1 Problem Domain

There is diverse distribution of video with respect to relevant semantic content. Video with lowest amount of meaningful content is surveillance video, since the relevant content is only the existence and identity of an intruder. More meaningful content can be found in sports event videos, documentaries, news broadcasts, advertisements and home videos with varying amount. However, the highest amount of semantics is in story-based videos. This kind of videos has a content based on a story line; they tell a meaningful story.

In addition to variety in amount of relevant content, there is also variety in techniques of presentation among videos as well. Content is transformed into a video through a process that is to be called *production*. In the context of this thesis, production's input is the content, and its output is the video. Anything that affects the final output is in the scope of production. It includes the camera in a surveillance video, or the writing of the script, acting, shooting, and editing in a movie.

Importance of production lies in the fact that differently produced videos are perceived differently. Two versions of the same movie can be remarkably different due to differences in casting, directing, and editing. Even regular and “director's cut” versions of the same movie, shot with the same cast by the same director, are distinct movies. Impact of production on the final output is powerful.

On the other hand, production has guidelines and conventions that limits and advises a producer. According to these guidelines, some video types are produced in a fixed way. For example, the presentation of a news program is similar to other news programs. An anchorman reads out a news item followed by the video clip related to the item. Sports event videos are also examples to videos of this sort. A soccer match is always recorded in the same way, with reverse angle shots, instant replays, and so on.

Contrary to these, some video types, such as movies are produced more freely. However, they still rely on conventions and guidelines that are recognized by the audience. Producers use these guidelines to get across their message to the audiance.

The semantic content diversity and production variety mentioned above necessitates different summarization approaches to be developed. For example, summarizing surveillance video may only consist of identifying parts of the video that contain the subject; robbery or intruder. On the other hand, summarizing soccer video might be possible by detecting goals and near-miss situations, and other events in the video that may be considered important by a viewer, such as bookings. In order to summarize story-based video, an automatic system might be built that catalogs parts of the video that tell an unbroken part of the story. A frame or a short clip can then be displayed in place of each story part, summarizing the video.

In order to identify important events in a soccer video, an automatic system might exploit the production methods unique to the domain, and detect slow motion replays in the video. Or the properties of the content can be exploited: The audio signal can be analyzed to identify the portions that have loud spectator noise.

In order to detect an intruder, the fact that a surveillance camera is targeted at a fixed location for a long period of time can be used. The background of the scene can be learned and the presence of an intruder can be deduced. In this situation, the behavior of the camera is a production property, while the background being fixed is a property of the content.

Production patterns and properties of the content being produced can be used to develop automatic summarization systems. Videos that share production patterns can be summarized using similar techniques; while it must be kept in mind that even videos that are produced in the same way have differences that will make summarization more challenging.

This thesis proposes two video summarization methods. One of the methods exploits production and content similarities between videos and the other relies on different properties of the scenes. Both methods' performances are compared against a clustering based summarization method.

2.2 Structure of a Video

Throughout this thesis, the term *'video'* is used to refer to the combination of an image sequence and its associated audio stream.

Continuous recording of a single camera in a video is called a *'shot'* [4]. Shots are the semantic building blocks in story-based videos. While editing raw shooting, editors divide the raw video into shots and combine these shots to build a story flow. Shots are analogous to letters in a language; in other words, they don't have meaning on their own, but they gain meaning as a sequence [5]. Single-shot scenes are exceptions, just like single letter words.

A collection of shots that are temporally adjacent and semantically related is called a *'scene.'* Scenes are sometimes called story units, in that they tell a part of the story that takes place in a fixed location, happens within a fixed time frame, involves a fixed list of people, or has a combination of these. Another characteristic of scenes is that a temporary resolution is reached within them [6].

For example, in the movie “Blade Runner,” there is a scene in which the main protagonist Deckard eats at a Chinese street bar. The first time the viewer meets Deckard is when the camera approaches him through the crowd in the street, and finds him reading a newspaper. In the next shot, we see the bar, and the next few shots are used to set up the place and time. At the seventh shot, Deckard gets up and crosses the street to sit at the bar. Four more shots are spent while he orders his meal. And finally after getting his meal, at the fourteenth shot, a cop comes and in seven more shots we learn that a certain Captain Bryant is looking for Deckard. Scene ends with Deckard smiling to himself knowingly.

The entire scene, a rather short one, lasts for twenty-one shots. Scene's time is fixed as well as the location, the street, but people involved in the scene change as shots progress. Deckard's smile provides the resolution by telling the viewer that he is not nervous, and releases the tension created by appearance of the cop.

Note that none of the shots by itself is able to move the story forward. Each shot provides background information, they help the user to form an idea of the place, the people, the things in the video, but shots by themselves do not have enough meaning to tell a story. However, when a shot is viewed within the context created by related shots, it becomes meaningful, and it can move the story forward [5].

In the above example, the shot that shows a cop appearing beside Deckard does not carry enough meaning by itself. The viewer does not know where Deckard is, does not know if the cop was around before, does not know if they have met before, does not know either one's purpose, and so on. Some of these mysteries are resolved, and the shot gains meaning, upon viewing the shots that come before and after it. It is learned they have not met before, cop has come to take Deckard to the police station and Deckard is not worried about it. All of this information along with details about the story (Deckard is eating Chinese food, the cop cannot speak English, it is raining, etc.) are told to the viewer only by the help of related shots. Shots that are adjacent in time and semantically related from scenes, and the story is told by scenes.

This relationship between shots and scenes has its roots in 'Film Grammar'. Film grammar is a collection of accepted rules and techniques which directors use to transfer the story form text to video [7]. Audiences worldwide are used to these techniques, and by employing them, directors are able to make viewers perceive the movie as a continuous experience, despite the appearance of several shot cuts each minute [8].

There are three types of scenes in story-based videos: Action scenes, dialogue scenes and dialogue scenes with action [6]. The director has infinite freedom over how to shoot a scene, but film grammar suggests a scheme.

A scene starts with an *establishing shot*. An establishing shot is usually a wide-angle view of the location, introducing the protagonists and their position in the scene. Different views of the conversing people, or the people participating in the action are shown as the scene progresses. The views are usually shot from varying distances, and the director may choose to show people in groups of different numbers, in order to break the monotony of the scene. In a dialogue scene, the camera gradually approaches people as a conversational climax is reached, and it backs up as a release. Re-establishing shots may be shown in the middle of the scenes to remind the location, the protagonists; or just as a break of monotony. Close-up shots of relevant objects in the scene, or views of relevant objects or places out of the scene can be shown. A scene usually ends with a re-establishing shot that acts as a conclusion to the scene [6].

Another important component of a video signal is the information stored in its audio part. Humans can understand what is happening in a movie only by listening to the audio track. The audio track contains speech, sound effects, music and environmental sound. Speech may belong to a conversation, or to a narrator. Sound effects accompany actions like walking or shooting. Music can be used to set a mood (creepy music), or signal an event or location (birthday, wild west). Environmental sound is used to support the reality of the story.

Speech is dominant in dialogue scenes. Usually all sounds are suppressed in a dialogue scene to keep the attention on the speech. Sound effects and mood setting music are most prominent in action scenes. Environmental sound and music used as introduction are strongest in establishing shots.

These properties of scenes, various shot types and relation between scenes and shots can be used to develop a method of video summarization.

On average, a film is made up of around 50 scenes, each having about 40 shots [5]. Adding this to the fact that shots in a scene are semantically related to each other, it becomes apparent that scenes are more suitable to summarization of story-based videos. Actually, when humans summarize a movie, they tend to tell the story scene by scene (e.g. Bryant greeted Deckard, and told him about four Replicants he needed to get retired) rather than shot by shot (e.g. Deckard came into the room and looked at Bryant. Bryant said “Hi ya, Deck.” Deckard replied “Bryant...”), as well. Summaries constructed using shots would be long and redundant, whereas scene-based summaries would be concise.

2.3 Overview of the Problem

The problem of automatic video summarization requires machines to identify the 'relevant' parts in a given video and present them in an easily accessible way. The difficulty of this problem lies in the task of automatically extracting meaningful information from digital data streams.

What can be automatically extracted from multimedia content is semantically low-level, in that the extracted clues have a relatively low amount of meaning by themselves. Examples are pitch, tempo or energy of sound signals, color, texture or shape information of visual signals, temporal relationships between signals, and similar information that can be obtained analytically or algorithmically. On the other hand, what is required from automatic systems is higher-level semantics, such as “Beethoven's 9th Symphony,” “red sports car,” “dialogue scene at 12:20.” An example that stresses this point is work by Smith and Chang, which states that 95% of the queries submitted to their search system *VisualSEEK* were semantic queries [3].

In the case of story-based video summarization, the first step to climb in the semantic ladder is detecting and isolating shots. As shots are the semantic building blocks of a story-based video, taking representative frames from each shot is a way to build a summary of the video. However, due to reasons explained previously, shot level summaries are not desirable, and in order to reach more useful and concise summaries, they need to be refined.

This refinement comes in the form of scene level video summarization. Although there is a large body of literature on shot boundary detection [9], efforts on automatic scene level video summarization have still not reached a conclusive solution.

2.4 Related Work

Various methods for automatic shot boundary detection have been put forward [9]. Since the visual properties on two sides of a shot boundary are expected to be different, it is usually visual properties that are exploited. These properties can be pixel differences or histogram differences of consecutive frames, number of changed edges in two consecutive frames, standard deviation of pixel intensities, contrast and so on [9]. Note that some of these features are more suitable to detect 'cut' type of scene boundaries, whereas others are specialized on detecting 'fades' or 'dissolves.' Applying thresholds to these features can be sufficient to get scene boundaries [9].

On the other hand, multiple features can be combined using classifiers so that a better detection is achieved [10].

If current research trends in scene level video summarization are investigated, it is seen that there are three main approaches to the problem:

- Object identification based approaches,
- scene type recognition based approaches, and
- video structure analyzing approaches.

Object identification methods generally aim to *index* video by identifying objects, producing object-based search opportunities. For example in [11], each shot is analyzed and its object-related properties are extracted. Depending on compositional conventions prevalent in video production and utilizing a Bayesian belief network, the authors determine the "focus of attention", the object that receives the most attention from the viewer. Interactions between objects are also determined [11]. These allow detailed object-based descriptions of shots to be made.

Another object identification based method is explained in [12]. The concept of probabilistic multimedia objects, "multijects," which are summarizations of time sequences of features that are extracted from multiple media, are introduced [12]. Multijects can be objects (e.g. car, helicopter, man), sites (e.g. forest, beach, outdoor), or events (e.g. explosion, ball-game). They are probabilistically modeled, with hidden Markov models and Gaussian mixture models, depending on them having temporal support or not respectively. They are allowed to interact, affecting likelihood values of each other. For example, presence of the multiject 'snow' makes the presence of the site 'outdoor' more likely, and the site 'underwater' less likely. This interaction is modeled by a factor graph [12]. In the end, meta data in the form of keywords are attached to the video stream, giving the multijects' likelihood, and spatio-temporal support.

The second approach is to classify scene types in a video. For example, the method explained in [13] involves building finite state machines for action or dialog scenes involving two people. Spatial arrangement of actors and camera positioning are the used features, and state machines are built according to observations made on dialog scenes and action clips, from the production point of view. Due to the fact that action scenes and dialog scenes are identical according to used features, authors use another criterion to classify scenes: average length of shots within a scene. Input videos are parsed with the state machines, and each scene's average shot length is calculated, effectively identifying and classifying scenes.

Controlled Markov chains are used to model temporal evolution of goals and non-goal situations in soccer videos in [14], thereby identifying goals in the video. All events are assumed to be two shots long. For each goal and non-goal situation (free kick, corner kick, etc), the camera motion properties (fast pan, fast zoom and lack of motion) of two consecutive shots are modeled in the controlled Markov chains. Likelihood value of each shot pair in the input video being generated by each Markov chain is calculated, and the chain that gives the highest likelihood determines the type of the situation. In order to further refine the classification, the pairs that have been classified as goals are ordered according to the amount of audio loudness increase between the shots. This ordering carries goal situations higher up in the ordered list [14].

Similarly, in [15], authors develop hidden Markov models that represent different scene types particular to baseball matches. The method is based on the idea that due to the production style of baseball videos most baseball highlights are composed of certain types of shots [15]. An edge descriptor that detects highly textured regions, color descriptors that detect the amount of grass and sand, camera motion descriptor, field shape descriptor and player height descriptor are used as features. Four models are developed for different ‘interesting’ situations in a baseball match. After features for each scene shot is extracted, the likelihood of each model for each scene in the baseball video are calculated using the Viterbi algorithm, and for each scene, the most likely model dictates the scene type.

An approach that models the entire structure of the video is in [16]. It uses hidden Markov models for capturing the structure of documentary videos, in their entirety. The features that are extracted and used as hidden Markov model observations for each shot are the shot type (static image, video clip or commentator) and camera motion (static, zoom and pan). Through training hidden Markov models with various topologies using the observations extracted, the authors analyze structures of various documentary videos. The conclusion reached is that there are structural differences not only between video genres but also within genres [16].

Another approach described in [17] uses a hidden Markov model that imitates the structure of dialogue scenes in story-based videos. Audio-visual features are used; existence of faces and audio class (speech, music, silence) are extracted for each shot. The observation sequence, which is nothing but the string of features for all shots, is segmented by the model using Viterbi algorithm, and captures dialog scene boundaries [17].

In [18] an unsupervised clustering method is used to generate table of content of a given video. The method uses histogram-based visual similarity and activity similarity measures. Histogram distances of the first and the last frames of each shot is used as visual similarity measures, whereas the average histogram distance between consecutive frames of a shot is utilized to be the activity value of the shot [18]. Using these measures, color similarities and activity similarities between the shots are calculated, taking into account their temporal differences. These shot similarities are used to cluster shots into groups using an "intelligent unsupervised clustering technique," which takes into account both the similarity measures, and the structure of the video. Basically, similar groups of shots that are interleaved in time are merged together [18]. As a result, a table of contents of scenes is generated. This method is compared against the proposed methods in this thesis. Results of comparisons are given in Section 5.4.

CHAPTER 3

PROBABILISTIC REASONING

Methods used in automatic reasoning can be classified into two categories: rule-based methods and stochastic methods [19]. Rule-based methods create a database of rules, which may have truth values attached, that define the environment and the ways with which these rules interact with each other. On the other hand, stochastic approaches attach uncertainties to “states of affairs” [19].

The locality and uniformity of interactions of rules are what makes rule-based systems attractive. If the interactions are simple enough, it is very easy to go through a list of rules and reach a conclusion. For example, a rule based system might define rules such as “birds fly,” “pigeon is a bird,” and so on. This way, starting from the information that something is pigeon, it is very easy to reason that it flies. One shortcoming of rule-based systems is the need to define exceptions to rules, such as “birds that are not ostriches, penguins, kiwis or dodos fly” (Actually it should approximately be “birds that are not ostriches, penguins, kiwis, dodos, chickens, turkeys, too young, injured or dead fly”). Still, if the rule base is well defined, and the environment is not changing, the reasoning process will be hassle-free.

However, it is also the rules and interactions of them that are the drawbacks of rule-based systems. First of all, using rules that interact uniformly strips one the ability of two-way reasoning - if A implies B, presence of B makes A more credible, and if A and C implies B, if B is present, finding out that A is true makes C less credible. If, for example, two rules are written such as “fire implies smoke,” and “smoke makes fire more credible,” these two rules would create a cycle and provide feedback to each other without any evidence but smoke. Implementing bidirectional inference required for these kinds of reasoning would mean sacrificing computational ease, as it would require brute force analysis of all rules and exceptions. Instead, most systems cut off cycles, permitting one-way inference [19].

Another advantage that is also a drawback concerning rule-based systems is locality. Rules interact locally; “if A is true then B (with certainty c)” means no further analysis is needed to assert B if A is known. Although providing computational ease, this property ignores possibility of correlated evidences. Assume a rule structure such as:

- If A is true then C is more credible,
- If A is true then B is more credible,
- If C is true then D is more credible,
- If B is true then D is more credible,
- If Z is true then C is more credible.

In such a case, when A is found to be true, it will affect D's credibility through both B and C, although the evidences of B and C are the same. Again brute force analysis of all rules is an impractical solution for this problem.

On the other hand, a stochastic system makes a declaration about the state of affairs, saying "most birds fly" with a statement such as $P(A|B) = p$. This statement is much cleaner than those made by the rule based system, as no exceptions are required. Also, bi-directional inference and correlated evidence are built-in features of Bayesian methods [19]. However, in this form, the stochastic statement is nothing more than an observation about the world. It is not suitable for making reasoning. Mechanisms that combine stochastic declarations and make decisions should be used. One such mechanism is the hidden Markov model.

3.1 Discrete Markov Processes and Extension to HMMs

3.1.1 Discrete Markov Processes

A continuous-time, continuous-state Markov process is characterized by the following equation:

$$P[x(t_n) \le x_n | x(t), t \le t_{n-1}] = P[x(t_n) \le x_n | x(t_{n-1})], \quad t_{n-1} < t_n .$$

The essence of this equation is that, in the Markov process $x(t)$, the past has no influence on the future, if the present is specified [20]. If $t_1 < t_2 < \ldots < t_n$, it follows that

$$P[x(t_n) \le x_n | x(t_{n-1}), \ldots, x(t_1)] = P[x(t_n) \le x_n | x(t_{n-1})] .$$

Discrete-state Markov processes, where the system can occupy a finite or countably infinite number of states, is called a *Markov chain*. Markov chains are useful in modeling systems that can be described as being in one of a set of states at any time, undergoing state changes according to a set of probabilities associated to the current state [21]. If the time instants at which state changes happen are regularly spaced, the Markov equation can be written as

$$P[x_n = S_j | x_{n-1} = S_i, x_{n-2} = S_k, \ldots] = P[x_n = S_j | x_{n-1} = S_i],$$

where state changes happen at $t_n = nT$, and the process x_n can occupy the states $S_1, S_2, \ldots, S_N$. Furthermore, the *state transition probabilities*, the right-hand side of the equation, are assumed to be time-invariant. They are denoted as:

$$a_{ij} = P[x_n = S_j | x_{n-1} = S_i].$$

a_{ij} is the time-invariant state transition probability from state *j* to state *i*, and it obeys the standard stochastic rules:

$$a_{ij} \geq 0,$$

$$\sum_{j=1}^{N} a_{ij} = 1.$$

In order to clarify the definitions, consider the following example:

A simple discrete Markov chain is used to model the weather. It is assumed that weather can occupy one of the three states SUNNY (state 1), RAINY (state 2) and SNOWY (state 3) at any time $(N = 3)$. See the Markov chain diagram in Figure 1.

Observations are assumed to be made once a day. Note the transition probabilities a_{ij} labeling transition arrows on the figure. Actual values for transition probabilities can be determined by observing the weather for a given period of time and counting the number of transitions from state *i* to state *j* and dividing that number by the total number of transitions from state *i*.

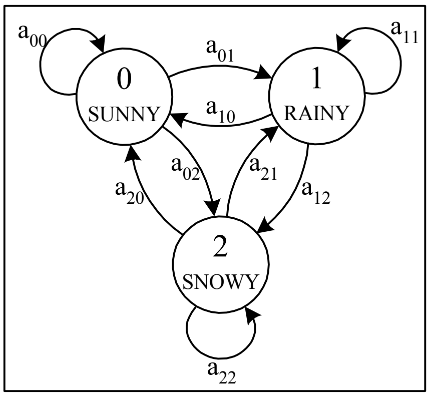


Figure 1. Example discrete Markov chain.

What this simple model gives us is the ability to make predictions about the weather by only knowing the current state. For example, if the current state is SUNNY, then the probability that it will rain tomorrow is a_{21}.

3.1.2 Hidden Markov Models

Before examining hidden Markov Models (HMM), consider a simple model for climate. Assume seasons are to be modeled, but the date is unknown. The only available information is whether the weather is SUNNY, RAINY, or SNOWY. This kind of a process, where the states are not observable, but a separate set of features are available for observation, is more suitable to be modeled by a hidden Markov model. States and state transition probabilities from discrete Markov processes are preserved in hidden Markov models. Observations are added as probabilistic functions of the state, and unlike discrete Markov processes, states are not observable. Idea is that the stochastic process being modeled can only be observed through another stochastic process.

In an HMM consisting of N states, state transition probabilities are shown by an N by N state matrix A, whose elements a_{ij} are the transition probabilities, as defined previously. For M observation symbols $v_1, v_2, \dots, v_M$, the observation probability matrix is B, with elements $b_j(k)$ defined as

$$b_j(k) = P[v_k \; in\, state\, n \mid x_n = S_j], \quad 1 \le j \le N \; and \; 1 \le k \le M .$$

The final parameter to describe the model is the initial state distribution. It is denoted by π, a 1 by M matrix, and its elements are

$$\pi_j = P[x_1 = S_j], \quad 1 \le j \le N .$$

Hidden Markov models are used widely in pattern recognition tasks. They are being applied to speech processing since 1970 [21]. In [22] an HMM based approach is used to recognize hand written characters. In [23] an HMM models the rate of milling tool wear. In the recent years, as video summarization gained importance as a research topic, HMMs are being utilized more frequently [11, 15, 16, 17, 24].

Before going on to the next section, climate modeling HMM example is given here, in order to clarify definitions. The model has four states, standing for the seasons: WINTER, SPRING, SUMMER, FALL. The observable is, as stated previously, the weather being SUNNY, RAINY, or SNOWY. A suitable topology for this model is given in Figure 2.

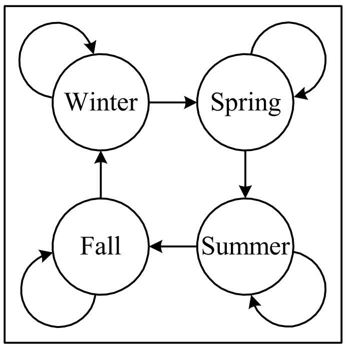


Figure 2. Example HMM topology.

In addition to the transition probabilities (a_{ij}) depicted in the figure as arrows, there are the observation probabilities $b_j(k)$. Again, estimates can be made regarding these probabilities. If it is assumed that measurements are made daily, the transition probabilities between consecutive seasons would be about $4/365$. Since no transitions are allowed between non-consecutive seasons, self-transition probability of a season to itself would be $361/365$. Note that the topology of the model forces season order.

Observation probability estimation would require long-term observation. Most likely, depending on the climate, probability of snowy days in summer will be very close to zero, rainy days will be most probable in spring and fall, and sunny days will be scarce in winter. A possible distribution is given in Table 1. Note that each column adds up to 1.

Table 1. Example HMM observation probabilities.

$b_j(k)$	j = WINTER	j = SPRING	j = SUMMER	j = FALL
k = SUNNY	0.1	0.3	0.7	0.3
k = RAINY	0.3	0.6	0.3	0.6
k = SNOWY	0.6	0.1	0.0	0.1

3.2 Basic Problems for Hidden Markov Models

Three problems are required to be solved for the HMMs to be useful in real-world applications [21]:

Problem 1. The first problem is finding the probability that a given observation sequence is generated by a given model. Given an observation sequence

$O = o_1 o_2 \ldots o_T$ and a model $\lambda = (A, B, \pi)$, find $P(O \mid \lambda)$, the probability of the observation sequence.

Problem 2. Given an observation sequence $O = o_1 o_2 \ldots o_T$, and a model $\lambda = (A, B, \pi)$, find the state sequence $X = x_1 x_2 \ldots x_T$ that best "explains" the observation sequence. Note that, apart from degenerate cases there is not a "correct" state sequence to be found. This problem is involved with the hidden part of the process being observed.

Problem 3. Adjust the model parameters $\lambda = (A, B, \pi)$ so that $P(O \mid \lambda)$ is maximized. This is the model training problem. The solution to his problem would enable one to optimally tune the model to a given observation sequence.

3.3 Solution to Basic Problems of HMMs

3.3.1 Problem 1

A procedure known as the *forward procedure* is used for calculating the probability of O given λ. First, forward variable $\alpha_n(i)$ is defined as the probability of the partial state sequence until time n and state i, given the model λ.

$$\alpha_n(i) = P(o_1 o_2 \ldots o_n, q_n = i \mid \lambda)$$

Note that the probability being looked for is

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i).$$

This probability can be found inductively.

Initialization: $\alpha_1(i) = \pi_i b_i(o_1), \quad 1 \le i \le N$

Induction: $$\alpha_{n+1}(j) = \left[\sum_{i=1}^{N} \alpha_n(i) a_{ij} \right] b_j(o_{n+1}), \quad \begin{cases} 1 \le t \le T-1 \\ 1 \le j \le N \end{cases}$$

Termination: $$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i)$$

The induction step takes into account that state j can be reached from all states, and calculates the probability of being in state j using $\sum_{i=1}^{N} \alpha_n(i) a_{ij}$. The multiplication with $b_j(o_{n+1})$ adds observation o_{n+1} into the picture. Recursion in $\alpha_n(i)$ makes it possible to calculate $P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i)$.

3.3.2 Problem 2

As stated before, a "correct" state sequence cannot be found for a given observation sequence. Rather, an "optimal" sequence is sought for, with different definitions of optimality. The most popular solution, *the Viterbi algorithm* finds the single best state sequence as a whole [21], maximizing $P(q \mid O, \lambda)$. In order to find this probability, a definition should be made.

$$\delta_n(i) = \max_{q_1, q_2, \ldots, q_{n-1}} P[q_1 q_2 \ldots q_{n-1}, q_n = i, o_1 o_2 \ldots o_n \mid \lambda].$$

Note that $\delta_n(i)$ is the highest probability among the probabilities of all single paths, at time n, accounting for the first n observations and ending in state i. $\delta_n(i)$ can also be written recursively as

$$\delta_n(j) = \max_{1 \le i \le N} [\delta_{n-1}(i) a_{ij}] \cdot b_j(o_n), \quad \begin{matrix} 1 \le n \le T \\ 1 \le j \le M \end{matrix}.$$

Viterbi algorithm is implemented using $\delta_n(i)$:

Initialization: $\delta_1(i) = \pi_i b_i(o_1), \quad 1 \le i \le N$

$\psi_1(i) = 0$

Recursion: $\delta_n(j) = \max\limits_{1\le i\le N}[\delta_{n-1}(i)a_{ij}]\cdot b_j(o_n), \quad \begin{matrix} 1 \le n \le T \\ 1 \le j \le M \end{matrix}$

$\psi_n(j) = \arg\max\limits_{1\le i\le N}[\delta_{n-1}(i)a_{ij}], \quad \begin{matrix} 2 \le n \le T \\ 1 \le j \le N \end{matrix}$

Termination: $P^* = \max\limits_{1\le i\le N}[\delta_T(i)]$

$q_T^* = \arg\max\limits_{1\le i\le N}[\delta_T(i)]$

Backtracking: $q_n^* = \psi_{n+1}(q_{n+1}^*), \quad n = T-1, T-2, \ldots, 1$

$\psi_n(i)$ is a matrix used for storage of most likely states at time $n-1$ that will transition to state i at time n. In other words, it holds the argument that maximizes $\delta_{n+1}(j)$ for all n and j.

3.3.3 Problem 3

Although the model parameters (A, B, π) that maximize the probability of an observation sequence cannot be solved for analytically, there are iterative methods that can locally maximize $P(O\,|\,\lambda)$. The Baum-Welch method is used in this work [21].

First of all, the backward variable must be introduced. Similar to the forward variable, backward variable $\beta_n(i)$ is the probability of observation sequence from $n+1$ to the end, being generated by the model λ, with state i when time is n:

$$\beta_n(i) = P(o_{n+1}o_{n+2}\ldots o_T \,|\, q_n = i, \lambda)$$

The probability of being in state i at time n is defined as

$$\gamma_n(i) = P(q_n = i \mid O, \lambda),$$

which can also be expressed as

$$\gamma_n(i) = \frac{P(q_n = i, O \mid \lambda)}{P(O \mid \lambda)} = \frac{P(q_n = i, O \mid \lambda)}{\sum_{i=1}^{N} P(q_n = 1, O \mid \lambda)}.$$

Using the fact that $P(q_n = i, O \mid \lambda) = \alpha_n(i)\beta_n(i)$ (probability of being in a state is equal to the combined probability of reaching the state from the start and the end),

$$\gamma_n(i) = \frac{\alpha_n(i)\beta_n(i)}{\sum_{i=1}^{N} \alpha_n(i)\beta_n(i)}.$$

Finally, the probability of being in state i at time n and in state j at time n+1 is defined as

$$\xi_n(i,j) = P(q_n = i, q_{n+1} = j \mid O, \lambda),$$

which can also be written using backward and forward variables as

$$\xi_n(i,j) = \frac{P(q_n = i, q_{n+1} = j, O \mid \lambda)}{P(O \mid \lambda)} = \frac{\alpha_n(i) a_{ij} b_j(o_{n+1}) \beta_{n+1}(j)}{P(O \mid \lambda)},$$

$$\xi_n(i,j) = \frac{\alpha_n(i) a_{ij} b_j(o_{n+1}) \beta_{n+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_n(i) a_{ij} b_j(o_{n+1}) \beta_{n+1}(j)}.$$

Note that the model parameters (A, B, π) can be calculated by counting event occurrences such as

$$\pi_j = \text{expected frequency of state } j \text{ at time } n = 1$$

$$a_{ij} = \frac{\text{expected number of transitions from state } i \text{ to } j}{\text{expected number of transitions from state } i}$$

$$b_j(k) = \frac{\text{expected number of } v_k \text{ observations while in state } j}{\text{expected number of times in state } j}$$

Also note that $\gamma_1(i)$ is the probability of being in state i at time $n=1$, $\sum_{n=1}^{T}\xi_n(i,j)$ is the expected number of transitions from state i to state j, and $\sum_{n=1}^{T}\gamma_n(i)$ is the expected number of times in state i. Using these, a set of re-estimation formulas are defined [21]:

$$\overline{\pi}_j = \gamma_1(j)$$

$$\overline{a}_{ij} = \frac{\sum_{n=1}^{T}\xi_n(i,j)}{\sum_{n=1}^{T}\gamma_n(i)}$$

$$\overline{b}_j(k) = \frac{\sum_{\substack{n=1 \\ o_n=v_k}}^{T}\gamma_n(i)}{\sum_{n=1}^{T}\gamma_n(i)}$$

Starting with an initial model $\lambda = (A,B,\pi)$ and using it to compute new model parameters $\overline{\lambda} = \left(\overline{A},\overline{B},\overline{\pi}\right)$, it is proven that either $\lambda = \overline{\lambda}$, or $P(O \mid \overline{\lambda}) > P(O \mid \lambda)$ [21]. That is, either the new model is the same with the old one, or it is a better estimation. Therefore, an iterative method to re-estimate model parameters by using $\overline{\lambda}$ in place of λ until there is no "change" in the model is feasible. This iterative re-estimation method gives a most likely estimate HMM. Initial model selection is important, as the procedure converges to a local minimum around the initial values.

CHAPTER 4

PROPOSED VIDEO SUMMARIZATION SYSTEM

4.1 Overview of the System

The proposed system consists of three stages, namely *preprocessing*, *feature extraction* and *decision making* stages, as shown in Figure 3.

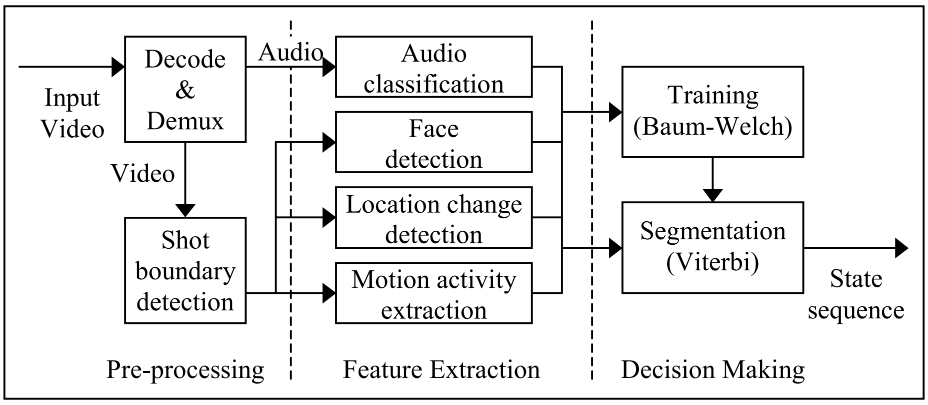


Figure 3. System Block Diagram.

Throughout the proposed system, video is processed shot by shot and preprocessing stage handles shot boundary detection. Feature extraction stage generates a feature vector for each shot, which is processed by decision making stage in order to summarize the video.

Decision making stage is the 'intelligent' engine of the system. It uses hidden Markov models (HMM) that take the feature vectors that are output in the feature extraction stage as observation symbols. In an HMM, observable symbols are assumed to be generated by an unobservable process. The HMM is a model of this unobservable process, and by observing the HMM information about actual process can be achieved. In the proposed system, the decision making stage treats the input video as the unobservable process. Through extracting features, and modeling the video by means of an HMM that is observing these features, the system segments the input video into its scenes.

It has been pointed out in Chapter 2 that different video categories require different summarization techniques. Similarly, the videos in the same category may have different properties related to summarization. Different sub-categories of videos may need different models, or different features may be useful in summarizing them.

For example, story-based videos are all based on a story, hence in order to summarize them segments that tell an uninterrupted part of the story should be identified. However, the method through which the story is conveyed changes according to the type of the video (film, sitcom), genre of the video (musicals, action films, dramas), and even to the director of the video.

A general method that takes all these factors into account and summarizes the given video is not feasible to build. However, a framework system may be built which can be adapted to the current input video. The first step in this adaptation is the definition of content types.

4.2 Content Types

The problem of summarizing different kinds of video is solved by flexible behavior of the decision making mechanism. *Content types*, classes of videos that can be summarized using the same features and the same model, are defined. Videos belonging to a content type, have some parallel properties that permit them to be processed similarly in the context of video summarization. It should be noted that content types are not genres or video types. A western series and a thriller movie can have the same content type, while two comedy movies can belong to different content types.

A set of features and an initial HMM can be associated with each content type. In such an approach the features and the model are determined empirically. Using different features and models allow the system to exploit production patterns and content characteristics of each content type. By supplying content type information, user is able to modify the behavior of the system.

Within the context of this thesis two content types are defined, and are elaborated below.

4.2.1 Dialog-Driven Content

Dialog-driven content can be defined as the type of story-based videos that are made up mainly of dialog scenes following each other to build a story. There may be action scenes within the content, but dialog scenes are in dominance. The obvious examples of this content type are situation comedies. Sitcoms are made up of shots of people conversing in different rooms, with an occasional shot reserved for signaling location or time changes. There are no action scenes, action is implied through conversations and settings. The story is based on conversations and the humor contained within them. Other examples of dialog-driven videos are dramas, and some other TV series. Films usually are not dialog-driven.

In order to segment scenes in a dialog-driven video, a number of characteristics can be exploited. Detecting location changes is useful, since scene boundaries typically occur at points the location changes. Identification of shots that do not belong to dialogs will be useful in catching time or location change shots. Speech and human face existence information can be used to segment dialog as shown in [17]. On the other hand, motion information will probably be useless, given that all dialog scenes exhibit similar motion characteristics.

4.2.2 Action-Driven Content

Action-driven content is the type of story-driven content in which the story is told through a mixture of dialog and action scenes. Dialog scenes are not as dominant as they are in dialog-driven content. Action scenes have a significant role in moving the story, and usually the final climax is solved in an action scene. In fact, action-driven content may depend more on action scenes to tell a story than it depends on dialog scenes. Cartoons are an example for this situation. All kinds of action movies, most cartoons, and some TV series fall into this category.

Obviously, motion information is one of the required features to properly identify dialog scenes (low motion) and action scenes (high motion). Location change information is also useful, since location change usually implies scene change.

4.3 Preprocessing

Preprocessing stage analyzes the video stream, and identifies shot boundaries. Since all processing is achieved on the shots as the atomic unit, identification of the shot boundaries is of utmost importance to the performance. An automatic method is used to detect shot-boundaries, and results of this method are manually edited to further refine the boundaries.

For shot boundary detection, an automatic method [10] works by clustering frames of the video into two classes using the 2-means algorithm on a two-dimensional feature space. The features are pixel difference and histogram difference between consecutive frames. By applying 2-means clustering, the set of all frames is segmented into boundary and non-boundary clusters.

In most cases this algorithm gives satisfactory results. However, when there are complex shot transitions, such as wipes or long dissolves, or cut-resembling events, such as flashes, the algorithm may fail to detect correct boundaries. Manual editing is useful in such cases. Shot boundaries identified in this stage are used throughout the whole system.

4.4 Feature Extraction Stage

The feature extraction stage analyzes preprocessed video and extracts the necessary features for each shot in the video. Output of this stage is a sequence of feature vectors, one feature vector for each shot in the video.

A maximum of 4 features are extracted for each shot: Face existence, audio class, location change existence and motion activity level. It is important to note that not all of the features may be extracted at all times. Features to be extracted are selected according to the content type of the video.

Some fundamental low-level features are standardized in MPEG-7. The feature extractors use the face, color histogram, motion activity and audio parameters, as descriptors from MPEG-7 [25].

4.4.1 Face Detection

Presence of human faces in video is an important clue in summarization. Action or dialog shots usually contain faces, whereas establishing shots seldom do. Scenes usually start and end with establishing shots, which are wide-angle views serving as the introduction or conclusion of the scene.

Face detection is quite a mature topic with diverse solutions [26]. Many methods employ techniques depending on isolating skin color regions in the input image, which provide a good initial estimate for the face regions, since the human skin color occupies a narrow region in any 3-D color space. The method used in the system applies a set of heuristic rules on color skin regions in order to detect faces [17].

Temporally regular spaced sample frames are taken from each shot, and connected regions of skin color in YUV color space are searched. Following table lists the boundaries of the skin-color region YUV space.

Table 2. Skin color region boundaries.

Skin-color bounds	**Magnitude (Min.)**	**Magnitude (Max)**	**Angle (Min)**	**Angle (Max)**
UV-space	0	100	130	170
YV-space	0	200	0	40
UY-space	0	200	225	260

The following set of geometric heuristics are also applied to each connected region of skin color:

- **Area:** The area of a connected face region should be less than a quarter, and more than 0.004 times the frame area. This heuristic eliminates extremely large or very small regions.
- **Aspect Ratio:** A connected face region should have an aspect ratio between 0.9 and 1.7. This heuristic eliminates some undesired regions with unexpected shapes.
- **Location:** A connected face region should be located *entirely* in the upper three quarters of the frame, without having any pixels closer to the sides more than 1/8 of frame width. Aesthetically, an important human face is not placed near the bottom or the sides of the frame [6]. This heuristic eliminates regions that do not obey this rule.
- **'Fullness':** Fullness is the ratio of the area of the connected face region to the area of the bounding rectangle of the connected region. The sides of a bounding rectangle are defined to be parallel to that of frames. A connected region should have a 'fullness' value more than 1/4. This heuristic eliminates strangely shaped regions, particularly crescent and tree shapes, which occur frequently but cannot be eliminated by the other heuristics.

If at least one connected skin color region passes all the heuristics defined above, the frame is assumed to have a face. If at least one frame in a shot has a face, than that shot is decided to be a FACE shot. All other shots are labeled as NOFACE shots.

4.4.2 Audio Analysis

Audio track contains a wealth of information relevant to the content of the video. Speech, sound effects, environmental sounds and even music can provide clues about the content. Humans can easily understand the occurring events in a movie by only listening to the audio track, merging the information they gather from dialogs, sound effects (e.g. gunshots, footsteps), environmental sounds (e.g. the sounds of a busy street) and music (e.g. creepy music when tension rises). Moreover, one can even keep track of events in action scenes, where speech is scarce, using other auditory clues.

The audio track can be used to aid in the process of automatic video summarization. A semantically high-level understanding of the audio signal (e.g. speaker identification, topic detection, scene segmentation) would enhance summarization performance considerably, but it is costly to reach such high-level semantics.

On the other hand, low-level properties of the audio track (e.g. short-time energy, fundamental frequency), which are less costly to extract, can improve summarization performance significantly, if carefully utilized [14, 17]. For example, in a typical soccer match the volume of sound increases when an important event takes place. In such a case, local energy of the sound signal can be thresholded to identify high-volume segments and used in sports content summarization [14].

Moreover, a number of low-level features can be merged together to reach a higher semantic description of the audio track. For example, in [27], the authors propose a method that utilizes energy, fundamental frequency and zero crossing rate of the signal to detect silence, noise, music and speech segments. Similar higher level descriptions of the audio segments can then be used in video segmentation.

In the proposed system audio content of each shot is determined using a method based on the method in [27]. Digitized content of each shot is divided into frames of constant length. Each frame is first analyzed to detect silent frames. Non-silent frames are then separated into speech and music categories [27]. A biased voting mechanism is then used to classify each shot into one of the classes SILENCE, MUSIC or SPEECH.

Reasoning behind this method is the possibility of modeling an audio signal as a linear combination of 4 signals (silence s[n], speech v[n], music v[n] and noise q[n]) [27]:

$$a[n] = a_s s[n] + a_v v[n] + a_q q[n]$$

Furthermore, the different characteristics of each signal can be summarized as follows [27]:

- Silence signals contain a quasi-stationary background noise, with an energy level lower than that of other signals.
- Speech signals contain voiced, unvoiced and plosive signals.
- Music signals are composed of sounds with 'peculiar' characteristics of periodicity.
- Noise signals are all signals that do not belong to the other categories.

Silence Detection

Each audio frame's energy is calculated according to the frame energy equation.

$$E[n] = \frac{1}{N_f} \sum_{i \in frame\, n} (a[i])^2$$

N_f is the number of samples in a frame, and a[i] is the digital audio signal. Dividing the sum by number of samples in the frame is for normalization. E(n) for each frame n is compared with a threshold, T_s to determine whether the frame is a silence frame or not. The threshold T_s is calculated using a buffer of silence frames using the same method as calculating frame energies.

$$T_s = \frac{1}{N_{buffer}} \sum_{i=o}^{N_{buffer}} (b[n])^2$$

The buffer contains N_{buffer} samples. Initially, the buffer is filled the first frames of the shot, which are assumed to be silent. As the frames are being processed, detected silence frames are inserted to the buffer replacing the oldest frames. Thus, the threshold is adjusted to changing silence levels within a shot.

In order to incorporate contextual information, a finite state machine (FSM) with K+1 states is used (see Figure 4). Using the contextual information enables the system to reject isolated frames. These frames are either low-energy frames within a high-energy sequence of frames, or vice versa; caused by momentary silences or noise.

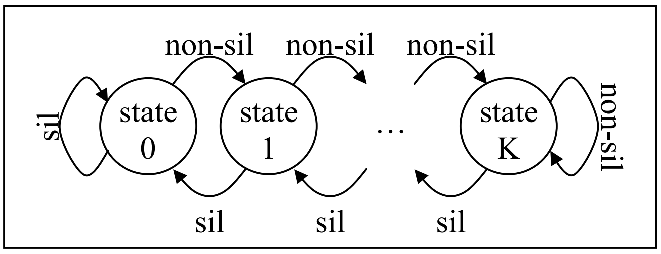


Figure 4. Finite state machine with K+1 states.

The first state in FSM, state 0, is the silence state, and state K is the non-silence state. All other states are 'inner states'. FSM is initially at state 0. After calculating each audio frame's energy and comparing with the current silence threshold of the shot, FSM moves one state higher; otherwise FSM moves one state lower. Frames that belong to inner states are not classified until a silence or non-silence state is reached. They are then classified according to the state reached [27].

Non-Silence Classification

After silence detection, non-silence frames are further analyzed to be classified into speech, music or noise. During this analysis, periodicity properties and zero crossing rates (ZCR) of frames are used, according to the following principles:

- Speech is composed of three classes of sounds: Unvoiced, voiced and plosive sounds.
- Unvoiced sounds have a low signal energy, no pitch and high frequency.
- Voiced sounds have greater signal energy than unvoiced sounds, and they exhibit periodicity over short intervals of time.
- Plosive sounds are transient with high energy levels, and they have no pitch.
- Music segments have a wider frequency range than speech segments.

- Music segments usually show periodicity characteristics with fundamental periods greater than that of voiced speech segments.

During the analysis, periodic frames are identified and, if the fundamental period falls within the fundamental period of typical music frames, they are labeled as music. Non-periodic frames are assumed to be noise. ZCR rate analysis of periodic non-music frames decides, if they are speech, music or noise.

Periodicity and fundamental frequency analysis of frames are achieved by taking autocorrelations of frames. Since the autocorrelation function can be thought to measure "shifted similarity", if the signal is quasi-periodic, the autocorrelation function has a significant local maximum on the fundamental period of the signal. Based on this concept, the autocorrelation function, $\varphi_N[n,k]$, is used to derive a periodicity measure [27]. $\varphi_N[n,k]$ is defined as

$$\varphi_N[n,k] = \sum_{i=-\infty}^{\infty} a[i]w[i-n]a[i+k]w[i+k-n] \quad , \quad n = lN_f$$

where $w[n]$ is a binary window:

$$w[n] = \begin{cases} 1, & 0 \le n \le N_f - 1 \\ 0, & otherwise. \end{cases}$$

The periodicity measure is

$$A_N[n] = \varphi[n,k_0]/\varphi[n,0]$$

k_0 is the index at which the first significant local maximum occurs (the fundamental period), and $\varphi[n,0]$ is the value of autocorrelation function at zero. Therefore, $A_N[n]$ is a measure of the 'strength' of the first peak. Note that for periodic signals, $A_N[n]$ has a value of 1. The autocorrelation function always has a maximum at 0, since a signal is identical to itself. All frames whose periodicity measure falls above an empirically selected threshold are classified as periodic.

Periodic frames, whose fundamental period falls between the expected range of the fundamental periods of music segments, are classified as music. The rest are speech candidates. Non-periodic frames are labeled as noise.

Zero crossing rate analysis is performed to classify speech candidate segments. Since speech segments are made up of voiced (periodic), unvoiced (non-periodic) and plosive (non-periodic) sounds, any speech candidate frame is concatenated with its non-silent, non-music neighbors. Analysis is made on this concatenation.

In a typical speech signal, the ZCR is expected to vary more than that of a typical music signal due to unvoiced and plosive, high-frequency sounds. For every speech candidate, its and its concatenated neighbors' zero crossing rates are calculated using the formula

$$ZCR(n) = \frac{1}{2N_f} \sum_{\substack{i \in frame\, n \\ i-1 \in frame\, n}} \operatorname{sgn}(a[i-1] \cdot a[i]) + 1$$

If the ZCR variance of the concatenated block is above an empirically determined threshold for speech segments, all concatenated frames are classified as speech frames. Otherwise, they are classified as music, if they are periodic, and as noise if they are not.

Finally, after each segment in a shot are classified into one of the classes silence, speech, music, or noise, a simple voting is performed among the segment results to obtain a single class for the shot, *speech*, *music*, *noise* or *silence*.

4.4.3 Location Change Analysis

Usually, a scene takes place in a single location. In a typical dialog scene, the director first introduces the viewer to the scene, the location and the people, by means of an 'establishing shot' [6]. An establishing shot usually provides a wide-angle view of the location. After the establishing shot, alternating views of the protagonists are shown as they converse. Shots of objects and places related to the conversation, or wide-angle shots of the location may be interleaved among these alternating views. The scene may be finalized by another wide-angle shot.

An action scene is similarly introduced, but the progression of shots in a scene is not as organized as in a dialog scene. Moreover, action scenes are less likely to take place in a single location and the single location may not be easily detectable in some cases. Consider a fight scene in a warehouse, or a gunfight in the main street of a Wild West town. Alternating shots will show different parts of the setting that are semantically linked, but have no low-level visual clue that they are actually in the same location.

Due to the complexity of detecting location changes in action scenes, the proposed approach attempts to identify location changes in dialog scenes and simpler action scenes.

The problem is approached by a windowed histogram comparison method. A fixed number of equally spaced frames are selected from each shot as samples. Color histograms of sample n, h_n, is calculated by

$$h_n(c) = \sum_{(x,y)\in image} B(x,y,c)$$

where $B(x,y,c)$ is a function that returns if the pixel at (x,y) is of color c.

A discrete temporal window, W_l, is defined. The window contains a fixed number, N, of samples. At each iteration of the algorithm, mean and variance histograms of the samples within the window are calculated. As a result of this operation a mean histogram, which has the mean value of each color for samples within W_l, and a variance histogram, which holds the variance of each color, are obtained.

$$h_m(c) = \frac{1}{N}\sum_{i=n}^{n+N-1} h_i(c)$$

$$h_v(c) = \sqrt{\frac{1}{N}\sum_{i=n}^{n+N-1} (h_i(c) - h_m(c))^2}$$

Mean histogram h_m and variance histogram h_v are used to determine if the sample in front of the window, h_{n+N} is similar to the ones in the window. D1 distance of histograms, absolute differences of color buckets, is used as a difference measure.

$$D_{n+N}(c) = \left|h_m(c) - h_{n+N}(c)\right|$$

This difference value is compared with product of the variance matrix and a threshold (T_{loc}). If the difference is larger than $h_v(c) \cdot T_{loc}$ for any color, sample $n + N$ is labeled as a location change sample. Otherwise, it is a non location change sample (see Figure 5). The window is moved one sample forward, and if there are more samples available, the algorithm is iterated.

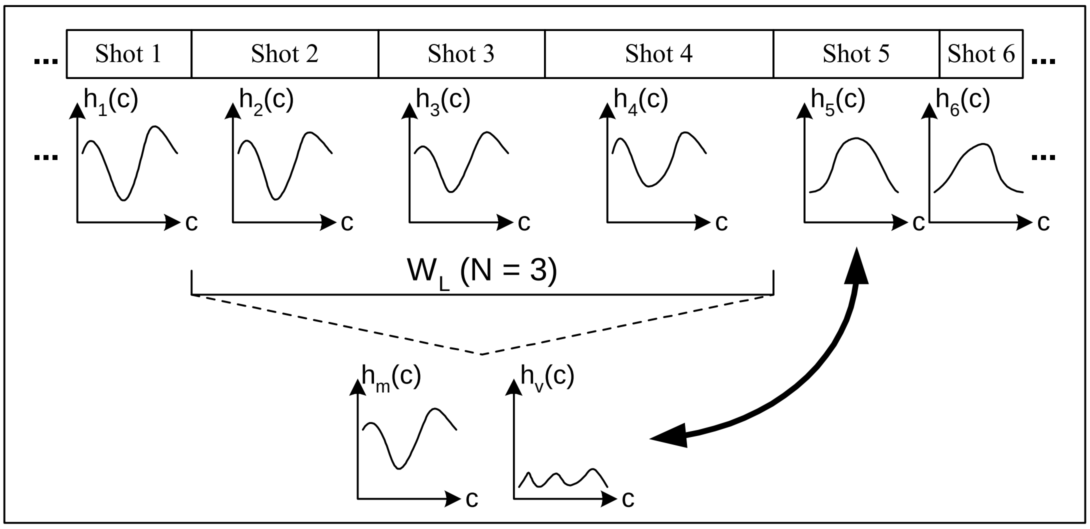


Figure 5. Location change detection method.

After labeling each sample, simple voting is applied between samples from each shot to determine the shot's label. If the total number of location samples is more than the number of *non location change* samples, the shot is labeled as a l*ocation change* shot. Number of samples taken from each shot, window size W_l, and threshold T_{loc} are empirically determined.

4.4.4 Motion Activity Analysis

There are two general types of motion in video. The first one is *global motion*, motion of the scene as a whole. The second is *object motion*, motion of objects in the scene, in such a way that can be identified from global motion. Global motion is generally caused by camera motion, such as panning and zooming. Object motion is also called motion activity.

Amount of object motion is an important feature in video summarization. Intuitively, it is expected that there should be more object motion in action scenes when compared to dialog scenes. Objective of this feature extractor is to obtain a qualitative measure of object motion in each shot.

In order to obtain the motion information in one frame of the video, block matching motion estimation algorithm can be used [28]. The frame, f_N, is divided into fixed size blocks, typically 8 pixels by 8 pixels. For each block b_n a search is made to find the most similar area in the next frame, f_{N+1}, of the video. The whole frame f_{N+1} is not searched; only a square area around the original position of the block b_n is checked, which is the search window W_s. Starting from the original position, all possible positions within W_s are evaluated according to a similarity measure, and the most similar position is assumed to be the position to where the pixels in f_N have moved to [28]. The similarity is decided by taking differences of the values of the pixels and summing their absolute value.

In order to obtain a quantitative measure for motion activity in each frame, variance of the magnitudes of all motion vectors in frame f_N is calculated [29]. Note that, by taking variance of motion vectors, one gets rid of most global motion that might be present in the frame. Through averaging motion activity values of all frames, motion activity value for the shot can be obtained. Finally, value for each shot is quantized into five levels, as suggested by the MPEG 7 standard [25].

4.5 Decision Making Stage

The decision making mechanism uses hidden Markov models to model the input video. Two different approaches are implemented for decision making. The first approach models the entire video using a hidden Markov model, whereas the second one models different types of scenes with different hidden Markov models.

In both cases, HMMs take the extracted features as observation symbols. States of HMMs correspond to shot types, as in *dialog shot, non-dialog shot, high action shot* and *establishing shot* and state transitions are assumed to be made at shot boundaries. Note that observation symbols are expected to have different observation probabilities in different states. For example, human faces are more likely to appear in dialogue shots rather than non-dialogue shots. Topologies, transition probabilities and observation probabilities of initial HMMs are determined so that they reflect actual video and scene structure.

The first approach to video summarization is based on identifying the type of each shot and detecting scene boundaries based on these shot types. A single HMM is used to label each shot in the video.

The second approach, however, identifies the scenes directly. Different types of scenes are modeled by different HMMs. The decision making mechanism tries to recognize both scene boundaries and the model that has the highest likelihood of having produced the observation symbols within the scene.

4.6 Models

Models for the first mode of analysis are built to represent entire videos. However, different models are used for different content types. This is expected to make the summarization system to adapt itself to the input video and produce better summarization performance. Three initial models are built for content type dependent video summarization. They use different features and have different topologies (see Figure 6). The features each model uses is explained in Section 5.2.

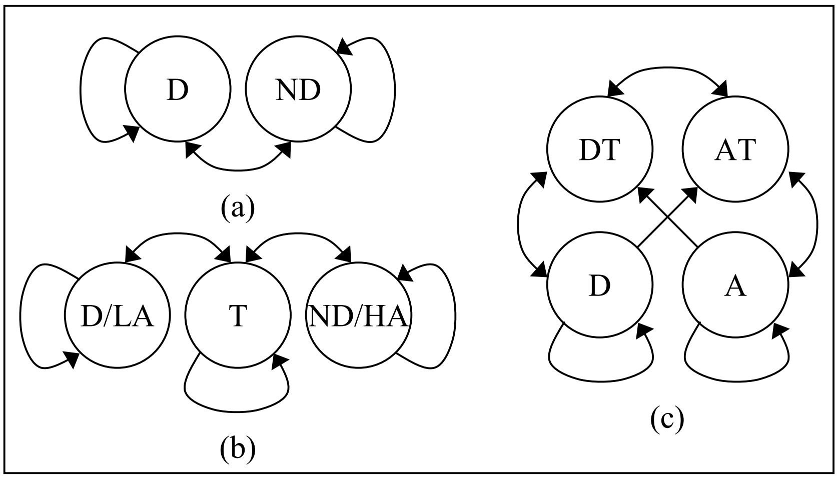


Figure 6. HMMs used in content type dependent video summarization. (D: Dialogue, ND: Non-dialogue, LA: Low-action, HA: High-action, T: Transition, A: Action, DT: Dialogue transition, AT: Action Transition)

For the second mode of analysis, video summarization based on scene modeling, HMMs represent individual scenes. Two basic initial HMMs are built; one for dialog scenes, the other for action scenes. Both HMMs are ergodic two state HMMs.

The dialog scene model uses

- Audio class,
- Face existence,
- Location change

features. Speech and face are the basic elements of a dialog, and thus the initial dialog scene model has a high likelihood of speech and face existence. Music and noise have lower observation probabilities, since dialogue scenes have dominant speech content [6]. One of the two states is selected to represent the establishing shot. Location changes have a higher probability of occurring in that shot, and face existence has a lower probability.

The action scene model uses

- Audio class,
- Motion activity

features. The audio class feature is used solely to distinguish action scenes, which typically have much less speech content when compared to dialog scenes. Observation probability of speech in the action scene model is low compared to music and noise, which are prominent characteristics of action scenes. Motion activity is used to implement the notion of establishing shot in an action scene. Establishing shots in action scenes tend to have lower motion content, when compared to action shots [6]. One of the states in the model is again chosen to represent the establishing shot. It should be noted that low motion shots might also appear during the course of the action scene unrelated to scene establishment [6].

All models' initial probabilities are defined based on the experience of the author and they are further trained to obtain better modeling. This training process is explained in the following section.

4.7 Training

HMM training has well-defined solutions [21], and the models in the system are trained using the well known Baum-Welch algorithm, which is explained in Section 3.4. However, the selection of the samples with which models are trained needs special attention. In video summarization, the usual approach is to train an HMM by other videos similar to the test video [11, 15, 16, 17, 24].

The approach taken for training in the first mode of operation, however, is slightly different. Before segmentation, each model is trained by the *test video* itself. The rationale behind this approach may be understood by recalling that each content type has an HMM that models the videos belonging to that content type, and that videos having the same content types have differences that may be relevant for summarization. For example, all action-driven videos are understood to be built up of dialog and action scenes. However, the frequency of action scenes, length of dialog scenes, usage of the camera, lighting, and sound, and many other properties are bound to be different in different action-driven videos. These differences are related to the script, the acting, the directing and the editing of the video and therefore they are unavoidable.

Note that these differences can also be modeled by HMMs. The frequency of action scenes, for example, is modeled by the transition probability from dialog shots to action shots. The length of dialog scenes corresponds to self-transition probability of a dialog shot. Usage of the camera changes the way the motion activity feature is interpreted. Scenes that are shot closer to the subject tend to have higher motion activity values than wide-angle scenes. This and other feature related differences are related to observation probabilities in an HMM.

Fortunately, a trained HMM is able to capture these differences and adapt itself to the movie. Through self-training the movie, models are able to capture the properties that are different among videos that belong to the same content type. This, in addition to good content type models, allows better modeling of the underlying process by which the video is generated, and thus provides a better performance. In fact, this process itself may not be called “training”, but simply a model “tuning”. As a result, better video models can be obtained.

In order to obtain better scene models, however, the usual approach is adopted. Initial scene models are trained with the observation sequences of sample scenes, and five scene models are obtained, two for each scene type.

CHAPTER 5

SIMULATIONS

Throughout the simulations a test set comprised of segments from four videos are used. All videos are recorded from Turkish Radio and Television (TRT) with an off-the-shelf PCI MPEG-1 encoder card. Two of the videos are Hollywood family movies, and belong to action-driven content type. The other two are Turkish-made serials belonging to dialogue-driven content type.

Parts that are not related to the story, such as commercial breaks, summaries of previous episodes, and credit sequences, are removed from each video. These parts have different structures and properties when compared to the rest of the video; commercials, for example, have much different auditory properties and camera usage. Likewise, summaries are often constructed by combining a few shots from each scene in the previous episode, in effect compressing the scene structure. Since they do not belong in the structure of the story, non-story parts of videos fall outside the scope of this study, and hence are not included in simulations.

Simulations are conducted in three phases. In the first phase, performance of the first video summarization method is evaluated. The second phase elaborates performance of the other method, which uses the likelihood values to classify the scenes in predetermined durations and the final phase compares these two approaches against the clustering based video summarization approach explained in [18].

In the first two phases, videos first have their shot boundaries identified by the automatic algorithm. After the boundaries are refined by an operator, necessary feature extractors are used to generate feature vectors for each shot. These feature vectors are fed to the decision making mechanism which produces shot type labels. Produced labels are processed one final time to get the result: scene structure of the video.

Scene structure is compared with a manually obtained ground truth scene structure, and precision and recall values are calculated as quantitative performance measures. Precision is defined as the ratio of the number of correctly identified scenes to the number of all identified scenes and recall is defined as the ratio of the number of correctly identified scenes to the number of scenes in the ground truth.

5.1 Feature Extractor Performance Simulations

Before examining video summarization simulations, performance of the feature extractors are briefly presented. Outputs of all four feature extractors are compared with subjective ground truth data from the test set. Table 3 shows results in terms of percentage of the shots correctly classified. Note that relatively simple feature extractors are used in the system in order to have less computational complexity.

Table 3. Feature extractor performance

Feature	Serial A	Serial B	Movie A	Movie B	Overall
Face	86.3%	83.0%	76.1%	56.4%	75.5%
Audio	75.5%	79.2%	71.8%	71.2%	74.4%
Location Change	88.2%	94.3%	85.6%	76.1%	86.1%
Motion Activity	100%	88.7%	72.9%	91.4%	88.3%

5.2 Content Type Simulations

In the first phase of the simulations, all videos in the test set are analyzed using different hidden Markov Models and feature sets. This analysis is done in order to evaluate performances of different models and features with different content types.

First of all, audio and face features are used to segment the video into dialogue and non-dialogue shots. More than 2-state topologies are not used, since more state (scene) types do not have any semantic meaning. The results (Table 4) indicate that audio and face features alone are not successful in segmentation of the sample set. Closer examination of the results reveals that the videos are highly under-segmented.

Table 4. Recall / precision values for different HMM topologies using audio and face features.

Audio, face	
Recall / precision	**2-state**
Dialog driven	0.139 / 1.000
Action driven	0.450 / 1.000

The next experiment adds the location change feature to the system, and this time 3- and 4-state topologies are used as well, since location changes imply transitions. The results in Table 5 show that dialog driven content is segmented quite well with this set of features, using the 2-state topology. Generally, dialog driven content is better segmented than action driven content with this feature set.

Table 5. Recall / precision values for different HMM topologies using audio, face and location change features.

Audio, face, location change			
Recall / precision	**2-state**	**3-state**	**4-state**
Dialog driven	1.000 / 0.742	0.778 / 0.489	0.584 / 0.548
Action driven	0.741 / 0.784	0.584 / 0.438	0.800 / 0.648

After adding the motion activity feature to the observation set, the performance decreases (Table 6). Scenes are observed to be over-segmented, although dialog driven content still has better results.

Table 6. Recall / precision values for different HMM topologies using audio, face, location change and motion activity features.

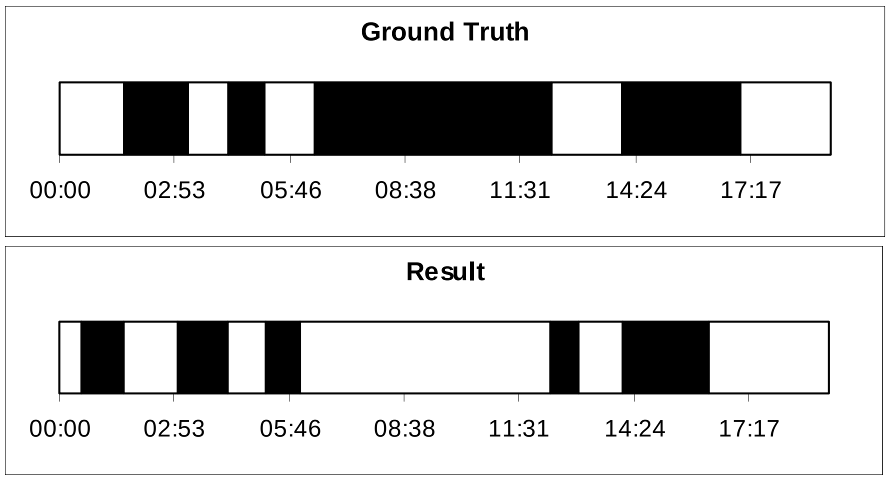
Audio, face, location change, motion activity		
Recall / precision	3-state	4-state
Dialog driven	0.750 / 0.430	0.611 / 0.389
Action driven	0.416 / 0.122	0.458 / 0.198

The final experiment in this phase involves motion activity and location change features, and topologies with more than two states. As observed in Table 7, this time content of action driven videos are segmented with 95% recall and 80% precision using a 3-state topology.

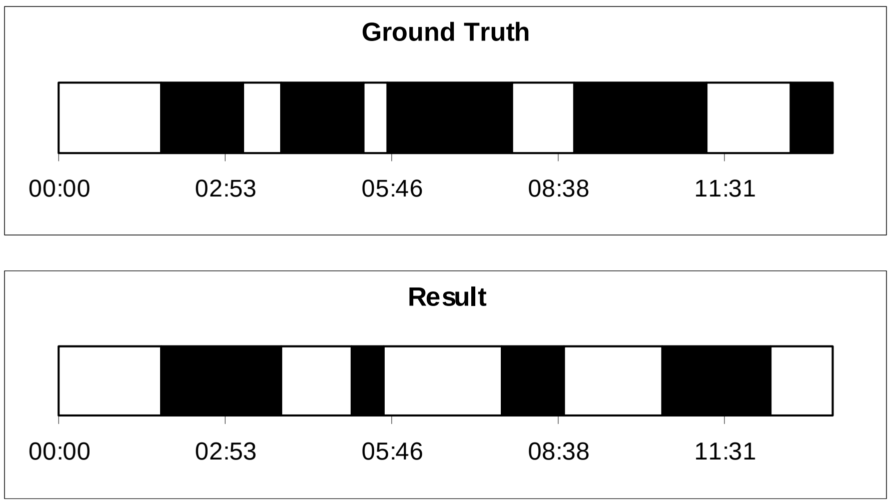
Table 7. Recall / precision values for different HMM topologies using location change and motion activity features

Location change, motion activity		
Recall / precision	**3-state**	**4-state**
Dialog driven	0.694 / 0.363	0.806 / 0.568
Action driven	0.950 / 0.800	0.742 / 0.800

These results indicate important conclusions. The second observation set (audio, face and location change) is suitable for segmentation of dialog driven videos. This is expected, since dialog driven video are made up mainly of dialogue scenes (face, speech and no-change), and non-dialogue shots (not face and speech), or location change shots acting as scene boundaries. On the other hand, the fourth observation set (location change and motion activity) is observed to be suitable for segmentation of action driven video, since they are comprised of scenes having different motion activity content. For this case, location change shots act as transition scenes and rest of the video is segmented into high-action and low-action scenes. The final point to emphasize is utilization of all features for segmentation degrades performance.



(a)



(b)

Figure 7. Sample simulation results a) Dialog driven, b) Action driven. Consecutive scenes are colored differently; the actual colors (black or white) are irrelevant.

Figure 7 shows two sample results from both content types. Video sequences are segmented into their scenes. The graphs show consecutive scenes in different colors. Scene boundaries (i.e. points at which colors change) are relevant, colors of individual scenes should not necessarily match between results and ground turth.

5.3 Scene Modeling Simulations

Second phase of simulations investigates the feasibility of modeling scenes for video summarization. Observation sequence input to the decision making module is divided into partitions of a fixed number of shots and each partition's likelihood of being created by each model is calculated. The model that has the highest likelihood is then used to segment that partition, and get shot labels.

Remember that five scene models are used in the system (see Section 4.6). Three of these models are dialog scene models and two are action scene models. Table 8 and Table 9 list precision and recall values for the partitions being classified correctly by dialog and action scene models, respectively. During this analysis, the actual class of a partition (i.e. ground truth) is determined by voting among its shots. If the number of shots belonging to action scenes are more than the number of shots belonging to dialog scenes, the partition is assumed to be an 'action partition.' A 'dialog partition' is defined similarly.

Table 8. Dialog scene precision and recall.

Precision / Recall		**Serial A**	**Serial B**	**Movie A**	**Movie B**	**Overall**
Partition size	**100**	0 / 0	1.00 / 1.00	1.00 / 1.00	1.00 / 0.50	0.75 / 0.63
	50	1.00 / 0.25	1.00 / 1.00	1.00 / 1.00	1.00 / 0.33	1.00 / 0.65
	25	1.00 / 0.57	1.00 / 0.94	0.82 / 1.00	0.85 / 0.75	0.92 / 0.81
	10	1.00 / 0.53	1.00 / 0.89	0.90 / 0.90	0.84 / 0.76	0.93 / 0.77

Table 9. Action scene precision and recall.

Precision / Recall		Serial A	Serial B	Movie A	Movie B	Overall
Partition size	**100**	0 / 0	1.00 / 1.00	1.00 / 1.00	0.67 / 1.00	0.67 / 0.75
	50	0 / 0	1.00 / 1.00	1.00 / 1.00	0.22 / 1.00	0.55 / 0.75
	25	0 / 0	0.50 / 1.00	1.00 / 0.60	0.75 / 0.86	0.56 / 0.61
	10	0 / 0	0.17 / 1.00	0.86 / 0.86	0.74 / 0.82	0.44 / 0.67

It should be noted that in Serial A, there are no action scenes, and in Serial B there is a single action scene. The low performance on Serial A is due to audio classification. The audio classifier misclassifies laughter effect in Serial A as music, boosting likelihoods of action models (action scene models prefer music and noise over speech, see Section 4.6). Therefore, although Serial A is composed entirely of dialog scenes, most of these scenes are misclassified as action scenes.

The method classifies 80 of the 97 partitions correctly, reaching an accuracy of 82.5% for the partition size of 10 shots. 34 of the 40 partitions (85.0%) are classified correctly for 25 shot partitions. These results are encouraging in the sense that correct partition classification ratio is quite high, even with low quality feature extractors.

However, partition classification cannot be used directly to achieve summarization. Summarization is achieved by locating scene boundaries, a job to which partition types can be helpful. A partition that is classified as 'action' is expected to be segmented better with an action scene model, especially the model which has the highest likelihood of generating that partition. Table 10 lists precision and recall values for all videos and partition sizes, achieved by segmenting each partition by the model that has the highest likelihood of generating it. After likelihood calculation and before Viterbi segmentation the model is trained with partition observation sequence for “tuning” (see Section 4.7).

Table 10. Precision and recall table for segmentation using scene models.

Precision / Recall		**Serial A**	**Serial B**	**Movie A**	**Movie B**	**Overall**
Partition size	**100**	0 / 0	0.50 / 0.33	0.60 / 0.33	0.43 / 0.25	0.38 / 0.23
	50	0 / 0	0.60 / 0.50	0.15 / 0.56	0.57 / 0.33	0.33 / 0.35
	25	0.75 / 0.43	0.15 / 0.40	0.17 / 0.44	0.23 / 0.27	0.33 / 0.39
	10	1.00 / 0.20	0.06 / 0.20	0.05 / 0.20	0.41 / 0.75	0.38 / 0.34

Low performance with Serial A is due to most of its partitions being classified wrong (see Table 8 and Table 9). The overall lack of performance is related to the partitioning method. Partitions are determined without any regard to the structure of input video. Therefore, a partition can have shots belonging to different scenes, and those scenes can be of different types. On the other hand, while segmenting partitions, all shots within a partition are assumed to belong to the same scene. A partition is segmented by a model which is trained on single-scene data. As a result, segmentation of partitions using scene models fails to reach the performance level of content type dependent video segmentation.

5.4 Comparison With Deterministic Approach

The performance of “semantic-level table of content construction technique” [18] is shown in Table 5. For the HMM-based method, the best performances for different content types are tabulated. For Type I content, audio, face and location change features are used with 2-state HMM topology, whereas for Type II content, location change and motion activity features on 3-state topology are utilized. Best performing scene modeling result (25 shot-long partition) is also given.

Table 11. Rule-Based vs. best performance HMM results

Recall / precision	**Deterministic [18]**	**HMM for Dialog driven**	**HMM for Action driven**	**Scene Modeling**
Dialog driven	0.806 / 0.410	1.000 / 0.742	0.694 / 0.363	0.450 / 0.415
Action driven	0.734 / 0.764	0.741 / 0.784	0.950 / 0.800	0.200 / 0.355

5.5 Evaluation of the Results

Results of content type simulations show that different models and feature sets are needed to better summarize different content types. This result is line with the definition of content types defined in Chapter 4, namely that different content types need different models and features for summarization. Better summarization is achieved by using a summarization scheme that takes the content types into account.

Scene modeling simulations suggest that classification of ‘partitions’ of videos can feasibly be achieved by scene HMMs. However, identification of scene boundaries, which is a prerequisite for video summarization, is not possible by the proposed method. It is understood that, in order to increase performance, a method that can determine both partition boundaries and partition types should be developed.

Finally, comparison of these three methods show that content type dependent video summarization method outperforms deterministic method for both content types. Using different models for different content types is due to the flexibility of HMM-based strategy, which is not possible for deterministic approaches. It is seen that scene modeling based method is not as competitive as the other methods.

CHAPTER 6

CONCLUSIONS

Story-based video summarization is an attractive research field with promising application areas. Shot level video summarization has attained a certain maturity. Scene level summarization, which aims to identify story segments in a story based video, is the natural summarization method and it is desired over shot level summarization; since it generates concise summaries, more similar to the way humans summarize a video. Unfortunately, unlike shot level summarization, which can be handled through processing low-level features only, scene level summarization requires combining semantically low-level features to reach higher-level semantic concepts.

Diversity of production techniques further complicate the problem. 'Production,' as defined in Chapter 2, is the process by which a story is transformed into a video. Different types of video, as in sitcoms and movies, are produced differently. Director's and editor's choices affect production as well. Moreover, video production industry has developed conventions that guide a director or editor in building the video. While summarizing story based videos, the differences and similarities in production should be taken into account.

In this thesis an automatic HMM based video segmentation system is presented. In the system, each video is analyzed to get four low-level features: face detection, audio classification, location change detection and motion activity. A feature vector for each shots of the input video is created with the results of the analysis. A decision making stage processes the feature vector sequence and assigns shot type labels to every shot. Hidden Markov models are used in the decision making stage.

Two different methods to video summarization are implemented. The first method uses a single hidden Markov model to segment the entire video. In order to account for different production techniques the system is configured according to *content types*. Two content types; dialog driven and action driven, are defined within this thesis. Content type dictates the particular features and model to be used in the system. The ability to adapt to the content type being analyzed is one of the core features of the system.

The model chosen for summarization of a video is trained with features of that video before summarization. This makes use of the HMM's capability to model video properties that are not dictated by the content type; the ones that are related to director's choices, such as camera usage and scene length. Together with the content type adaptation, self-training enables the system to fine tune itself to its input. The need for using different models and features for the two content types is demonstrated by experiments.

For the second approach, the scenes instead of videos, are modeled by the decision making hidden Markov models. After feature extraction, the feature vector sequence is divided into fixed length partitions. For each partition, all models are tried, and the one that gives the highest likelihood of generating the partition is selected as the representative model of that partition. Partitions are then segmented with their representative models, after self-training. Partition summaries are combined to get a video summary. Identifying scene types is central to this approach.

Finally, proposed methods are compared against a clustering based video summarization method [18]. Content type dependent video summarization method enjoys the highest performance, and scene identification based method is the least successful method.

Dialog driven and action driven content types do not span all story based videos. More content types can be defined as an improvement to the system. Enlarging the scope of the system to non-story based videos is another option. In order to obtain a full-fledged video summarization system, more sophisticated feature extractors that have higher performance can be used.

On the other hand, a technique that identifies scene types and segments scene boundaries can be developed. Scene identification of the second method suggests that such a technique could enhance performance.

REFERENCES

[1] The Internet Movie Database, http://www.imdb.com.

[2] Dyne:bolic, http://dynebolic.org.

[3] M. R. Naphade and T. S. Huang, “Extracting Semantics From Audiovisual Content: The Final Frontier in Multimedia Retrieval,” *IEEE Trans. on Neural Networks*, vol.13, no. 4, pp. 793-810 July 2002.

[4] J. V. Mascelli, H. Gür (transl.), “Sinemanın 5 Temel Öğesi,” İmge Kitabevi Yayınları, 2002.

[5] B. T. Truong, S. Venkatesh and C. Dorai, “Scene Extraction in Motion Pictures,” *IEEE Trans. on Circuits and Systems for Video Technology*, vol. 13, no. 1, pp. 5-15, January 2003.

[6] D. Arijon, “Grammar of the Film Language,” Silman-James Press, 1991.

[8] F. Germeys, “Film Perception,” http://www.psy.kuleuven.ac.be/labexppsy/ top/ filipweb/ research2.htm.

[7] C. Dorai and S. Venkatesh, “Computational Media Aesthetics: Finding Meaning Beautiful,” *IEEE Multimedia*, The Media Impact Column, vol. 8, no. 4, pp. 10-12, October-December 2001.

[9] R. Lienhart, “Comparison of Automatic Shot Boundary Detection Algorithms,” *Proc. Image and Video Processing VII*, 1999.

[10] M. R. Naphade, R. Mehrotra, A. M. Ferman, J. Warnick, T. S. Huang, A. M. Tekalp, "A High Performance Algorithm For Shot Boundary Detection Using Multiple Cues," *IEEE International Conference on Image Processing 1998*, 1998.

[11] A. M. Ferman, A. M. Tekalp, “Probabilistic Analysis and Extraction of Video Content,” *IEEE International Conference on Image Processing 1999*, 1999.

[12] M. R. Naphade, I. V. Kozintsev, T. S. Huang, "A Factor Graph Framework for Semantic Video Indexing," *IEEE Trans. on Circuits and Systems for Video Technology*, vol. 12, no. 1, pp. 40-52, January 2003.

[13] L. Chen, M. T. Özsu, "Rule-Based Scene Extraction From Video," *Proc. of IEEE International Conference on Image Processing 2002*, vol. 2, pp. 737-740, 2002.

[14] R. Leonardi, P. Migliorati, "Semantic Indexing of Sports Program Sequences by Audio-Visual Analysis," *to appear in IEEE International Conference on Image Processing 2003*, September 2003.

[15] P. Chang, M. Han, Y. Gong, "Extract Highlights from Baseball Game Video With Hidden Markov Models," *Proc. of IEEE International Conference on Image Processing 2002*, vol. 1, pp. 609-612, 2002.

[16] T. Liu, J. R. Kender, "A HMM Approach to the Structure of Documentaries," *IEEE Workshop on Content-based Access of Image and Video Libraries 2000*, pp. 111-115, 2000.

[17] A. A. Alatan, A. N. Akansu, W. Wolf, "Multi-Modal Dialogue Scene Detection using Hidden Markov Models for Content-based Multimedia Indexing". *Int. Journal on Multimedia Tools and Applications, Kluwer Ac.*, 2001.

[18] Y. Rui, T. S. Huang, S. Mehrotra, "Constructing Table-of-Content for Videos," *Multimedia Systems, Special section on Video Libraries 7*, pp. 359-368, 1999.

[19] J. Pearl, "Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference," Morgan Kaufmann Publishers, 1998.

[20] A. Papoulis, S. U. Pillai, "Probability, Random Variables and Stochastic Processes," McGraw-Hill, 4th ed., 2002.

[21] L. R. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257-286, February 1989.

[22] H.-S. Park, B.-K. Sin, J. Moon, S.-W. Lee, "A 2-D HMM Method for Offline Handwritten Character Recognition," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 15, no. 1, pp. 91-105, 2001.

[23] R. K. Fish, M. Ostendorf, G. D. Bernard, D. A. Castañon, "Multilevel Classification of Milling Tool Wear with Confidence Estimation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 1, pp. 75-85, January 2003.

[24] L. Xie, S-F Chang, A. Divakaran, H. Sun, "Structure Analysis of Soccer Video With Hidden Markov Models," *Proc. of IEEE International Conference on Acoustics, Speech, and Signal Processing 2002*, vol. 4, pp. 1096-1099, May 2002.

[25] B. S. Manjunath, P. Salembier, T. Sikora, "Introduction to MPEG-7," John Wiley & Sons Ltd., 2002.

[26] M.-H. Yang, D. J. Kreigman, N. Ahuja, "Detecting Faces in Images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 24, pp. 34-58, 2002.

[27] C. Saraceno, R. Leonardi, "Identification of Story Units in Audio-Visual Sequences by Joint Audio and Video Processing," *Proc. of IEEE International Conference on Image Processing 1998*, pp. 363-367, 1998.

[28] A. M. Tekalp, "Digital Video Processing," Prentice Hall Signal Processing Press, 1995.

[29] K. A. Peker, A. Divakaran, T. V. Papathomas, "Automatic Measurement of Intensity of Motion Activity of Video Segments," *SPIE Conference on Storage and Retrieval for Media Databases*, vol. 4315, pp. 341-351, 2001.