# COMMERCIALS DETECTION USING HMMS

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**ABSTRACT**

This paper presents a system that automatically detects TV commercials using HMMs. To that end, two different observations are taken for each video shot: logo presence and shot duration. These observations are modeled using HMM and the Viterbi decoder is finally used for shot labeling. The system has been tested on several hours of real video achieving more than $99\%$ of correct labeling.

## 1. INTRODUCTION

The availability of cost effective means for digitizing video and the reduction of costs for digital media storage has led to the introduction of new home video devices that can record hundreds of hours of TV programs. In this context, audiovisual analysis tools that help the user to manage this huge amount of data are very important in a very competitive market to introduce the recording devices.

Among other analysis tools, detection of TV advertisements is a topic with many practical applications. For instance, from the point of view of a TV end-user, it could be useful to avoid commercials in personal recordings. In another possible scenario, a TV-viewer can could make *zapping* during commercials receiving a notification from the system when the commercial break has finished.

Most previous works on commercial break detection [1, 2] have based their strategies in studying the relation between audio silences and black frames as an indicator of commercials boundaries. The analysis is performed in either compressed [1] or uncompressed [2] domains. In [3] also specific country regulations about commercials broadcast is used as a further clue. Another interesting approach is presented in [4], where overlaid text trajectories are used as a clue to detect commercial breaks. The idea here is that overlaid text (if any) usually remains more stable during the program time than in the case of commercials.

Our approach to commercial detection relies on two simple observations to label each video shot as a *Commercial* or *Program* shot. The first observation is based on the fact that TV logos are removed during commercials (at least in the Spanish broadcasts). The second observation stems from the fact that video shots tend to have a shorter duration within commercials. These observations are modeled using HMM and the Viterbi algorithm is finally used to label each shot. One advantage of the proposed scheme is that it can be easily extended with more different observations, such as differences on the audio volume. However, in this paper, only the two previous observations are used.

The rest of this paper is organized as follows. In Section 2 a general overview of the system presented in this paper is given. Section 3 describes the proposed scheme used to detect the location of video logos which is one of the cues used by the system as mentioned above. Section 4, describes the shot labeling using the HMM. Finally, Some results and conclusions presented in Section 5.

## 2. SYSTEM OVERVIEW

The system proposed in this paper, can be regarded as a three-state machine. The names of these states are: *Initialization*, *Commercial* and *Program*. Changes between these states only occur at the shot bounds, and obviously, shots are labeled according to the current state. Fig. 1 sketches the general flowchart of the state machine.

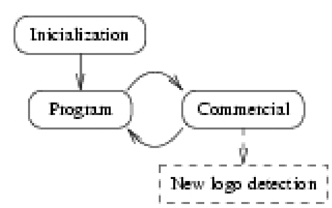



**Fig. 1**. General block diagram of the commercial detection system

The *Initialization* state occurs during the system set up only. The goal of this state is to extract a binary mask that indicates the region where the TV logo is placed. Whenever a logo mask is detected the system changes to the *Program* state. From this point on, the system is always either in the *Program* or *Commercial* state. Transitions between these two states are based on a Viterbi decoder that takes shot-based measurements as observations as explained in Section 4. An important requirement of the system is that it has to be robust to changes in the logo position (sometimes the logo moves to a different corner) or changes in the logo pattern. To accomplish this requirement, the system starts a parallel process whenever the current state changes to *Commercial*. The goal of this process is to check if a new logo mask is being used. In case that a new mask is found the system is forced to change back to the *Program* state. If no new logo mask is found and the Viterbi decoder changes the state back to *Program* this parallel process is stopped.

## 3. LOGO MASK EXTRACTION

This section describes our algorithm used to detect TV logos by the *Initialization* and *Commercial* states. In general, TV logos can be grouped into opaque, transparent or animated. In this paper, we have only considered the case of opaque and transparent logos. This is justified because currently animated logos are not as frequent as the other types. However, we will see that the proposed approach is general enough to be used even with animated logos.

Intuitively, we say that a logo exists if we can find an area in the image with *stable* contours. Notice that in this definition we focus on the area containing the contours and not in the contours themselves, therefore this definition also applies to the case of animated logos, considering the area that comprises the moving contours.

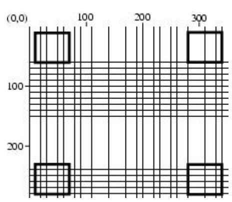



**Fig. 2**. The boxes indicate the areas where logo search is performed using CIF resolution

The logo search is restricted to the four corners as shown in Fig. 2. For each corner a separate search is conducted and the process is stopped when at least one logo has been found. The process for one of the corners is summarized in Fig. 3. First, shot detection is used to extract one frame per shot. Let $F_i$ be that frame where $i$ indicates the number of shots processed. Then, the gradient of $F_i$ is taken and the result is time averaged:

$$S_i = \frac{i-1}{i} S_{i-1} + \frac{G_i}{i} \tag{1}$$

where $G_i$ is the gradient image of $F_i$. The next step includes thresholding of $S_i$ and morphological processing to reduce spurious pixels and fill holes. Morphological processing includes operations such as closing, opening and morphological area filtering [5]. The result of the morphological processing is a binary mask as shown in Fig. 4.

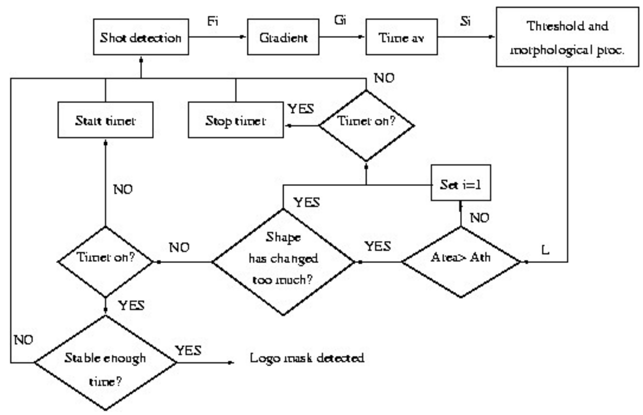
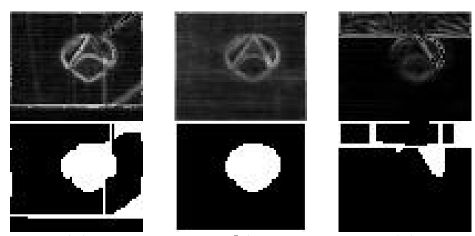



**Fig. 3**. Blocks diagram used to detect TV logos

Notice that the idea of using just one frame per shot instead of processing evenly spaced frames is very important to reduce the influence of very long shots in $S_i$. This allows to reduce the time needed to remove spurious contours in $S_i$ and hence the time to obtain the logo mask.



(a) (b) (c)

**Fig. 4**. Examples of logo mask extraction. The first row shows the time averaged gradient $\mathcal{S}_n$. The second row shows the corresponding masks. (see text for explanation).

Once the binary mask $\mathcal{L}$ has been obtained, two different tests are performed to check if the detection process has concluded. The first test checks if the area of the binary mask is over some threshold. If the area of the binary mask is too small as in Fig. 4.c, the search procedure is reset (i=1). This is a common situation when the search procedure has started during the commercials. The second test checks that the mask shape remains stable for a specified time (at least 3 min.). This test guarantees that enough data has been gathered to extract the logo mask. Fig. 4.a shows an example where too few frames have been processed. As the number of frames processed increases the logo shape stabilizes and finally a logo mask can be extracted as in Fig. 4.b.

## 4. SHOT LABELING

As introduced in Section 1, shot labeling is based on two observations shot duration ($T_n$) and logo presence ($L_n$), where $n$ indicates the shot number.

Logo presence is measured for each shot using only one frame (the last one). Let $\mathcal{G}_n(i,j)$ be the result of the gradient of this frame and let $\mathcal{L}(i,j)$ be the logo mask obtained as described in the previous section, where $\mathcal{L}(i,j) = 1$ for the logo pixels and zero elsewhere. Then, $L_n$ is computed as the mean value of the image gradient under the logo mask given by the following equation:

$$L_n = \frac{\sum_{i,j} \mathcal{G}_n(i,j).\mathcal{L}(i,j)}{\sum_{i,j} \mathcal{L}(i,j)} \qquad (2)$$

where the summatories are extended to all image pixels. A possible question at this point might be why using only one frame per shot. The answer is twofold. First, to reduce the computational burden. Second, preliminary examples have shown that using shot-based measurements did not produce a significant increase in the system performance, since as we shall see in Section 5 errors come from different sources.

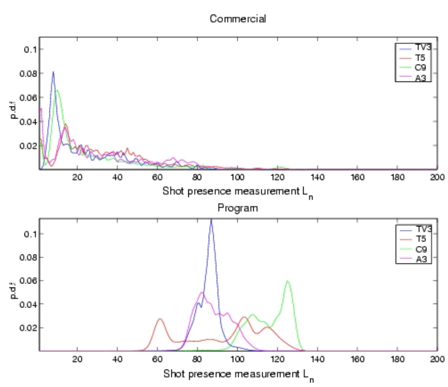


**Fig. 5**. p.d.f of the logo presence measurement $L_n$ for commercials (above) and program time (below) extracted from four different TV stations.

Figures 5 and 6 show the histograms of the logo presence measurement $L_n$ and the shot duration $T_n$. This histograms have been extracted from four different TV stations. From the figures, it is easy to conclude that $L_n$ is more useful to the labeling process since the distributions of $H(L_n|p)$ and $H(L_n|c)$ are farther apart ($p$ and $c$ indicate the state *Program* and *Commercial* respectively). Actually, our experiments have shown that the shot duration observation is only useful for labeling programs like talk shows where usually long shots are performed.

As introduced in Section 1, the process is modeled using a HMM with two states, and then, the Viterbi algorithm is used to perform the shot labeling. Following the notation as in [6], a HMM is characterized by a set of parameters:

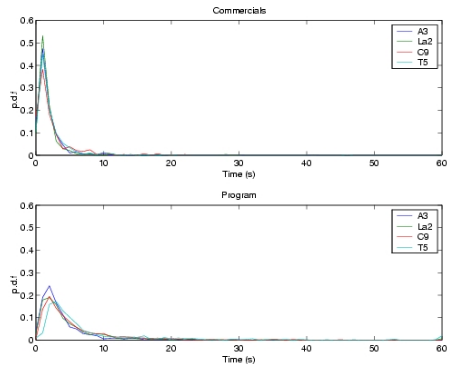


**Fig. 6**. Shot duration p.d.f for commercials (above) and program time (below) extracted from four TV stations.

$$\lambda = (A, B, \pi) \qquad (3)$$

where $A$ is the transition matrix, $\pi = \{\pi_c, \pi_p\}$ are the a priori probabilities for each state, and $B = \{b_c(O_n), b_p(O_n)\}$ are the observation probability distributions for each state given the observation $O_n = \{S_n, L_n\}$. The set of parameters $\lambda$ has been estimated from more than 10 hours of manually labeled TV recordings. Using this data, the values of $\pi$ are estimated as the percentage of time corresponding either to program or commercial, the matrix transition $A$ is obtained using the mean number of shots per program or commercial block, and the density functions $B$ are modeled using multivariate Gaussian Mixture Distributions (GMM) using diagonal covariance matrices. The parameters for each GMM are obtained using the EM algorithm. Fig. 7 shows an example with the probabilities $b_c(O_n)$, $b_p(O_n)$ input to the Viterbi decoder, where it can be seen how the probabilities effectively change depending on the underlying state.

## 5. RESULTS

The system described in this paper has been tested on 6 different Spanish TV stations. Some of them use opaque logos and other transparent. To evaluate the results we have defined three parameters:

- False acceptance (FA), percentage of the time that the system miss-classifies programs.
- False reject (FR), percentage of the time that the system miss-classifies commercials.
- Correct classification, percentage of the time that the system makes the correct classification.

The results obtained using the previous definitions are gathered in Table 1. Fig. 8 shows the outputs of the Viterbi

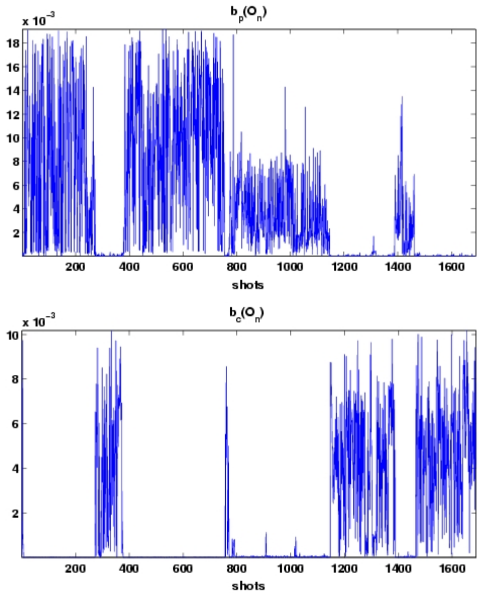



**Fig. 7**. Conditional probability values $b_c(O_n)$, $b_p(O_n)$ input to the Viterbi decoder.

| TV Station | Total time | % FA | % FR | % Correct |
|---|---|---|---|---|
| Tele5 | 7161 s. | 0.43 | 0.05 | 99.52 |
| Ant3 | 7149 s. | 0.21 | 0.26 | 99.53 |
| C9 | 7091 s. | 0.01 | 0.39 | 99.60 |
| Tve1 | 7158 s. | 0.15 | 0.25 | 99.60 |
| La2 | 7018 s. | 0.37 | 0.05 | 99.58 |
| Tv3 | 7173 s. | 0.6 | 0.06 | 99.34 |

**Table 1**. Labeling results obtained for 6 TV stations

decoder for two different examples. In Fig. 8.a the output obtained for the last sequence of Table 1 is shown. It can be seen that in this example the system makes the correct labeling for most of the time. The two errors found in this example are common to the other sequences. The missed commercial break (false reject) was caused by a brand logo placed in the same location that the program logo (see Fig 9.a). Next a false acceptance error is found. In this case the logo was very similar to the image background yielding too small values of $L_n$ (see Fig 9.b). Fig. 8.b shows the robustness of the system to changes in the logo position. In this example, the logo changes its position from one corner to the other around the second 4000. Initially, the system changes its state to *Commercial* and starts the logo search process as described in Section 1. It can be seen that after a short time the system finds the new logo and then changes back to the *Program* state making the right decision.

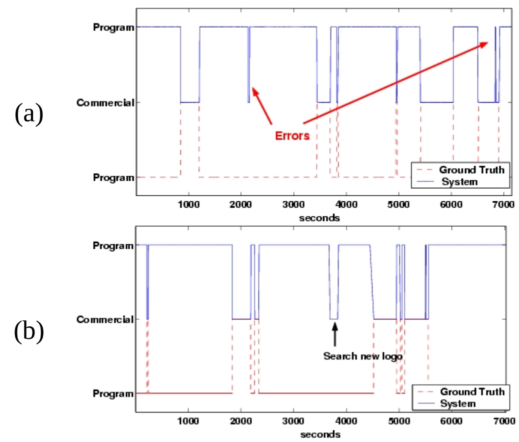



**Fig. 8**. Output of the Viterbi decoder: a) for the TV3 channel of Table 1, b) when the TV station is changed.

(a) (b)

**Fig. 9**. Examples of errors: a) false reject, b) false acceptance.

## 6. REFERENCES

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