An algorithm for enhancement of audio content classification

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ABSTRACT

Presently, fast proliferation of information enforces novel challenges on content management. Further, computerized audio classification along-with content description is considered as valuable method to manage audio contents. In general, classification involves two steps. First, is the processing of accessible data in economical ways to deliver explanatory features. Second is how accurate features of undetermined tests is evaluated to choose classifier. In this paper, k-neighbor algorithm with machine learning is proposed for feature extraction as well as content classification/description. This algorithm enhances Quality of Service parameters of classifiers. Here, development of training as well as testing data set is developed to increase the classifier accuracy. A test engine set-up bed using simulation tool MATLAB is designed to estimate the implementation performance of the algorithm. A range of features are studied to evaluate effectiveness in terms of accuracy, zero crossing rate (ZCR) and spectral roll frequency. From the experimentation results, it is observed that the proposed algorithm can achieve accuracy of 95.8% for 2 sec window length as compare with k-neighbor algorithm. A total enhancement of 11% is achieved with cross validation error of 29.6. A superior assortment of training fabric to extract few additional useful features can enhance accuracy further.

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1. INTRODUCTION

Information is extremely important in our daily lives. This information is needed for everyday activities such as watching or reading the news, listening to the radio, or watching a video. It's difficult to find what you're looking for due to the massive amount of information available. Thus, content-based audio classification deals with audio content analysis. Audio content-based categorization and retrieval for audio-visual data parsing is still a thrust area. The researchers are still designing as well as develop fully functional audio-visual systems for audio/video content parsing of multimedia streams. The fast growth of information necessitates new content management requirements, such as media archives and consumer products. People currently conduct database searches using various meta-tags. It uses brief text constellations to describe large pieces of data. The meta-tags are created by a variety of people. It has been discovered that how meta-tags are interpreted varies from person to person. The goal of automatic audio description systems is to improve content management. Commercial content management software is already available. However, many potential uses remain unexplored. Commercial interest is piqued by the promise of audio categorization and content description technology. Media companies require efficient technology storage, retrieval, and search. Customers require efficient media consumption methods. Thus, developing algorithm to manage information is a need of time.

Automatic audio description system is used as a tool for content management. It simplifies daily routines involving information management. This effort is part of a wider audio categorization and content description research project. It is necessary to comprehend audio content classification and feature extraction in this case. Audio categorization and feature extraction are intertwined in a variety of fields. In MATLAB, a testbed for content categorization algorithms is created. The goal is to create a broad framework for comparing different classification techniques. It helps to determine their performance and provides investigation for further enhancements of content classification algorithms. This paper consists of five sections. The literature review is outlined in the section 2. Section 3 explains a content management as well as a testbed. Section 4 discusses the creation and evaluation of a classifier, while section 5 discusses the conclusion.

2. LITERATURE SURVEY

The need for more advanced content management with new methods to analyze and categorize audio is presented in this section. However, most content management applications are quite complex. In general, audio classification and segmentation are considered as a powerful tool for content management. It is also useful in various audio processing and to improve video contents. An audio clip consists of several classes. It may consist of music tailed by speech. Hence, segmentation of the audio clip helps to find the starting of music and speech begin. Thus, segmentation improves classification. A general audio classification scheme to segment an arbitrary audio clip is presented in [1]. It achieves good accuracy rate of 96%. Classification is done in two steps. The first step discriminates the audio as speech as well as non-speech segments. In the second step, speech segments are processed to find changes in speaker. Whereas, non-speech segments categorize music, environmental sounds and silence. Research by Bashar *et al.* [2], a scheme is presented to classify the audio into seven categories. It is able to attain accuracy over 90%. Research by Jawaherlalnehru and Jothilakshmi [3], a hierarchy of audio classes is proposed to limit the number of classes that a classifier must classify between. An accuracy of 61% is achieved for ten music genres. A speech as well as music classifier is presented in [4]. An accuracy of 98.6% on 2.4 sec long analysis lengths is achieved.

Music classification needs to extract features such as instrument timbre. It helps to recognize pitch, tempo, and chord of respective instruments. A computerized music classifier can be designed with these features. On the other hand, Spectral attributes are leisurelier to estimate. Hence, are considered for experimentation. Research by Wang [1], music is separated in three categories. First is popular music domain. Second belongs to jazz group. Third is a category of classical music. Average accuracy of 45% is presented. Feature extraction of MPEG layer 3 encoding standards is presented in [5]. It helps to provide raw clip of audio speech for experimentation with 91% accuracy. Research by Su *et al.* [6], long audio clip of 10 sec is used to attain all harmonic components in each audio spectrum. It achieved total 82% group accuracy. Research by Rodd *et al.* [7], audio browser is described to segment audio contents. They showed that segmentation accuracy depends on the quality of audio clips. Error rates in the range of 1-14% is achieved. A technique to determine indices of video clip is presented in [8]. A method to recognize music at low signal to noise ratio proposed in [9] helped for commercial owners in television domain. Segmentation technique to understand the effect of change in speaker voice with the help of Markov model is described in [10]. Further, speech recognition based on Markov process for speech recognition is presented in [11], [12]. Noticeable percussive audio contents to extract rhythmic structures is presented to enhance music classification in [13]. A technique to understand different instrument sound of MPEG-7 is described in [14], [15]. A computerized sound monitoring system is described to detect intruder in [15] for surveillance applications. The technique that helps to structure audio and ease labelling the segments in expressed in [16]. A statistical method is proposed to extract features of audio contents is presented in [17]. Here, vocal music is not considered for experimentation. Research by Wu *et al.* [18], music summarization algorithm is used to cluster segmented frames. It resulted in better accuracy. A humming method to estimate melody features is presented in [19]. Further, segmentation as well as pitch stalking approach is considered for feature extraction in [20]. It can achieve 90% accuracy on 10 notes query. The basis for content management is knowledge extraction from the media. In practice, audio clips contain countless differences and similarities. It in turn increases the complexity of audio content classification. Schwarz *et al.* [21] introduced the developments and technical aspects of current standardization effort. Kesavan *et al.* [22] presented the advancement and architecture of adaptive http streaming delivery as a web-based service delivery approach. Girish *et al.* [23] proposed a method to identify the type of audio present at each node. Alzubi *et al.* [24] presented data analytics method which enables computers to learn and do what comes naturally to humans, i.e. learn from experience. Soofi and Awan [25] provided a comprehensive review of different classification techniques in machine learning. Narkhede *et al.* [26] implemented support vector machines (SVM) by learning from input samples to classify music into separate classes of music genres. Sreekala *et al.* [27] proposed a GWOECN-FR approach which is primarily concerned with reliably and rapidly recognizing faces in input photos. Cyril *et al.* [28] proposed an automated learning with CA-SVM based sentiment analysis model that reads the Twitter data set. Mulani and

Mane [29] implemented fast, secure, and areaefficient AES algorithm on a reconfigurable platform. Mulani and Mane [30] suggested implementation of fast and area efficient discrete wavelet transform (DWT) oriented invisible image watermarking system integrated with cryptography on reconfigurable platform. Kashid *et al.* [31] proposed a device which is beneficial for measuring temperature, and humidity.

3. PROPOSED ALGORITHM

Audio classification as well as content description includes various methods. Figure 1 shows a test engine model to extract features and automatic classification of audio contents. An observed data-sequence is stored in database. This does not approximate any information contents. A pre-processing of this sequence can segregate precise characteristics. It is stored in a feature vector. It comprises numerous eloquent measures that helps to classify the sequence into distinct classes. The available data-base is pre-processed to attain informative features such as training as well as testing data. A biggest challenge is the develop an algorithm for efficient feature analysis of un-known samples.

A signal processing algorithm is proposed to separate information from the observed sequence. However, a feature as the spread of the frequency spectrum in the audio range for classification. The second step is learning. Significant decision boundaries are attained by learning. In general, there are two techniques to learn classifiers. One is known as supervised learning. The second is un-supervised learning. After training, comes classification process. Clustering method is considered for classification. To enhance the accuracy, decision boundaries are selected on feature values. Thereafter, error rates are estimated based on extracted training as well as testing data. Till today, there is no feature available that can distinguish various classes with full conviction. The effectiveness of every feature is approximated with cross authentication on the training set data. It is observed that low error rates imply that the feature is effective.

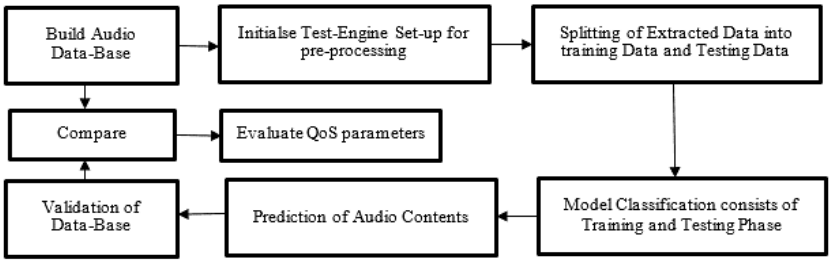

Figure 1. Test engine model to extract and classify audio contents

A k-nearest neighbor (KNN) classifier with Q-learning mechanism is considered in this work. It is known as an instance based classifier. It performs decisions founded on the relationship amid the unknown and stored samples. It helps to classify audio contents into different categories. Here, all training samples are merely stored in a multi-dimension euclidean space. All feature values are considered in the same region. It is observed that features with low values has slight relevance in attainment of relationship. To enhance the performance of the algorithm, normalization of feature values as well as axis weighting is considered.

Algorithm: to estimate performance of audio content classifiers
Input: define directory path, audio file format, size_hop and size_window
Output: estimate data to generate a set of training and label those samples

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1. Start
2. Build a database
   - Sampled audio clips are stored in directory
   - Long audio clips are splitted to have efficient use of memory in feature extraction process.
   - Evaluate desired features that are named as sorted data-base
3. Initialize the proposed test-engine to set all needed paths
4. Develop frame_work to extract various features. Here new features are added.
5. Generate result_vector of size A by B. Here, A is feature dimensionality. Whereas B represents time index for every value of features.
6. Implement classification algorithm to predict the audio contents and estimate classifier performance
7. End

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4. RESULTS AND DISCUSSION

A test engine set-up in MATLAB is implemented in this paper to design audio content classifier. The quality of service (QoS) performance is evaluated. In this section, a depiction of the used evaluation and design procedure is charted. The proposed evaluation method aims to get universal evaluation results. In the design procedure, a comparison of feature's efficiency is shepherded. Here, a few feature sets are proposed. A database of audio is collected to evaluate the performance of various features. It consists of 2 hours of data from audio recordings. It consists of male as well as female. All audio contents are sampled at 44 KHz rate. Every sample is represented with 16 bits. In general, database is divided in two parts. One consists of training set of about 72 minutes. The other contains testing set of 48 minutes. A proper care for not considering data of same male or female is taken in both the sets. It helps to evaluate the performance with greater accuracy. In the design process, features are designated to constitute feature vectors with greater efficiency. Further, efficiency is estimated only on the training data set. The features are not evaluated on the testing set. At the end, final evaluation of the classifiers performance is done on the testing set. Hence, give a good estimate of the accuracy of the classifiers. The KNN needs to adjust the k-value.

The conclusion is that the data set considered for experimentation is stored features. It has attained 94.7% accuracy. Here for analysis, window lengths taken is 1 sec. Further, database in audio band with the proposed algorithm is able to achieve 92.1% accuracy. The window lengths is varied in steps of 0.1, 0.5 and 1 sec. In general, extracting vivid features of audio perception is a challenging task. Following three features are considered for audio content classification chores. In a processing window, zero crossing rate (ZCR) as (1) helps to find total time territory of zero crossings. The total sample count is represented by S. Further, y(s) is sth sample value. For positive arguments, sign value is one. Otherwise, it is considered as zero.

$$Zero\ Crossing\ Rate = \frac{1}{S-1}\sum_{s=0}^{S-1}\left|sign\big(y(s)\big) - sign(y(s-1))\right| \quad (1)$$

The energy volume in the signal is represented with root mean square (RMS) as (2). It represents the sum of squared data sequence in time domain.

$$Root\ Mean\ Square = \sqrt{\frac{1}{S}\sum_{s=0}^{S-1} y^2(s)} \quad (2)$$

In (3) helps to determine the distribution level of energy in audio frequency spectrum as given. Here, B(n,k) represents discrete fourier transform of nth frame in a spectrum. It is a significant feature used for audio content classification.

$$Spectral\ Roll-off\ Frequency(n) = max\left(p\left|\sum_{k=0}^{p} B(n.k) < Threshold\sum_{k=0}^{K-1}|B(n.k)|^2\right|\right) \quad (3)$$

Steps: to add more features as well as classifiers

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1. Perform parameter passing with input as well as output arguments.
2. Store this changed file in the defined directory.
3. Execute start-up file to use these added features
4. Run file to implement new features
5. Repeat steps 1-4
6. Thereafter, new features are stored in classification file
7. Set all paths for the proposed test engine set-up to use new classifier scheme

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Figure 2 shows the flow chart of test-engine structure for audio content classification. Figure 3 represent feature space. The variance of RMS is on y-axis. Whereas variance of ZCR is changed on x-axis. It is observed that proposed system can discriminate audio contents more effectively. The change in variance value from 0 to 0.025 can discriminate audio spectrum. Figure 4 represent two dimensional feature space. The spectral roll-off frequency is represented on y-axis and SCR ratio on x-axis. Here the features values are mixed. The proposed algorithm can create decision boundary as shown in Figure 5. It helps to classify audio contents. Further, a dimensional space with spectral roll-off frequency on the y-axis. Whereas ZCR ratio is varied on x-axis. Here, standard deviation of all feature values is normalized. It helps to get a well weighted feature space. A cross validation classification accuracy for extracted feature set by considering window size for 2 second is shown in Figure 6. For change in values of k, accuracy is measured. It is observed that there is a little difference in classifier performance. Table 1 presents comparative analysis of proposed algorithm with k-neighbor algorithm. The proposed algorithm is able to provide accuracy enhancement of 6%.

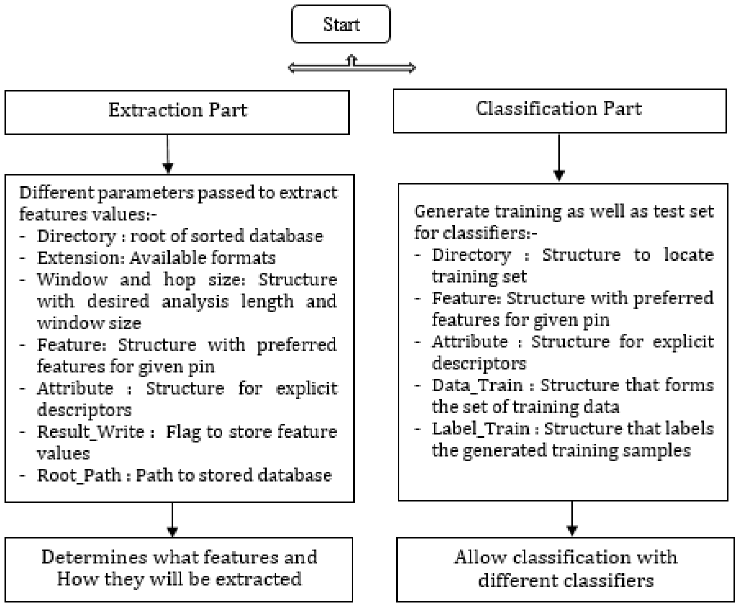

Figure 2. Flow chart of test-engine structure for audio content classification

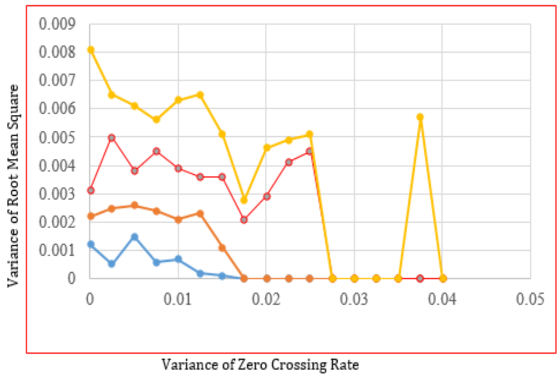

Figure 3. Graph of variance of RMS vs variance of ZCR

Figure 4. Graph of RMS vs ZCR ratio

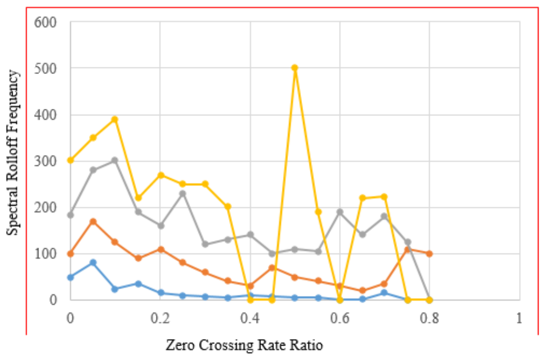

Figure 5. Graph of spectral roll off frequency vs ZCR ratio

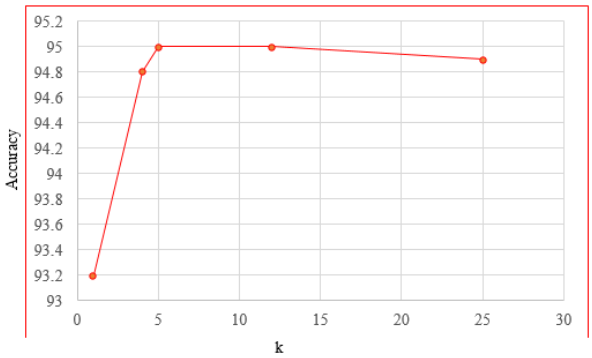

Figure 6. Graph of accuracy vs k-values

Table 1. Performance of classifier

Classifier type	w=0.1 sec	0.5 sec	1 sec	Error
k-nearest neighbor	74.3	84.2	88.1	33.4+/-1.8
Proposed algorithm	79.3	92.1	94.7	25.2+/-0.7

5. CONCLUSION AND FUTURE SCOPE

Content description as well classification is an expansive field. It considers different content management methods. Further, there are four major techniques to support users working in the media applications. First is a classification method. Second is known as segmentation. Third is used to recognitize the audio contents. At the last, summarization approach is considered for enhancing QoS performance. An machine learning approach for computerized based audio content categorization is proposed in this paper. Here, test engine set-up in Matlab is considered to test and validate the algorithm. Audio content discrimination is a complex process. First, knowledge of feature extraction as well as classifier is needed for lucrative classification. Second, features that maximizes the discrimination among various classes is to be selected. Here, QoS performance considered for audio classification such as zero-crossing rate, different spectrum measurements and short-term energy. It works by extracting feature values. Third, is design a classification algorithm to make predictions on extracted feature values. A KNN algorithm with-learning mechanism is presented. Fourth, volume of information of added samples that are collected to make predictions. It vastly verifies the classifiers performance. Following are the observations: i) classification accuracy is evaluated for varying window length size, ii) performance optimization with minimum iteration to enhance classification accuracy with machine learning approach, and iii) performance of the k-nearest drops declines in number of instances.

Future scope: a better collection of extracted data can further enhance accuracy. Still better QoS performance can be achieved by considering more audio clips to train classifier. Automatic segmentation of audio as well as video clips is also able to increase classification.

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