Asian Journal of Information Technology 16 (6): 383-391, 2017
ISSN: 1682-3915


# A New Optimal Feature Selection Scheme with Orthogonal Polynomials and Ant Colony Optimization for Content Based Video Retrieval System

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**Abstract:** In this study, a new optimal feature selection scheme with orthogonal polynomials and Ant Colony Optimization (ACO) for Content-Based Video Retrieval System (CBVRS) is proposed. Initially, the video file is divided in to smaller number of chunks as shots in orthogonal polynomials transform domain. In order to identify the key frames to represent a shot, each video image inside a shot is then applied with same orthogonal polynomials to yield Direct Coefficients (DC) images. In this research, the DC image which has the maximum DC value is modeled to be a key frame. From the identified key frames, low level feature such as color, edge and texture information are extracted in the same orthogonal polynomials domain. Since, the extracted features are larger in size, ACO scheme is adopted to select optimal features that represent a key frame for content-based video retrieval system.

**Key words:** Ant Colony Optimization (ACO), CBVRS, feature selection, orthogonal polynomials, optimal, scheme, information

## INTRODUCTION

Dimensionality reduction also termed as “feature selection” is one of the main problems in the field of image mining. It is a process of finding optimal features to represent the entire dataset by eliminating irrelevant and redundant data (Hayat *et al*., 2014; Tiwari and Jain, 2014). By this way, the performance of an image/video retrieval system increases considerably with lesser space and computation time. There are only two broad classifications of feature selection scheme namely filter and wrapper methods. The algorithm that accomplishes selection task independently comes under filter scheme whereas in wrapper methods, the algorithms are bound to rely on the fitness function.

These two classifications are divided into sub categories viz. forward selection, backward elimination, forward and backward combination, random choice and sample based method. The forward selection scheme iteratively adds the feature if the criteria are satisfied and removal of irrelevant feature is carried out with backward elimination. Both addition and removal is allowed in combination of forward and backward approach. Random selection initially may start with all features or empty for evaluation. Heuristic function is deployed in sample based method for evaluating the extracted features (Chen *et al*., 2013; Li *et al*., 2013; Qablan *et al*., 2012; Deriche, 2009). The selection of optimal features plays a vital role in image processing applications such as content-based image retrieval, content-based video retrieval, facial recognition and Iris recognition systems and many such feature selection schemes have been reported in the past. Saxena and Dubey (2015) reported a detail survey on feature selection algorithms that include Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Principal Component Analysis (PCA), Genetic Algorithm (GA) and Neural Networks (NN). Kanan *et al*. (2007) adopted ACO to select optimal features for face recognition system.

Further, it is been compared with traditional Genetic Algorithm (GA) in terms of feature selection method and efficiency. Babatunde *et al*. (2015) extracted feature with Local Binary Pattern (LBP) that are further subjected to ACO for selecting the best feature sub set. In addition to that, this technique has been deployed for Face Recognition System (FRS) application and its performance is also reported. Rashmi *et al*. (2014) developed an image retrieval system that extracts color, texture and shape features to form a feature vector. Since, the dimension of feature vector seems to be large, ACO has been adopted in this research to select optimal features. Similarly, implemented an image retrieval system that extracts

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features with the help of co-occurrence matrix, autocorrelation, energy and homogeneity (Varghese, 2010). These features are then forwarded to ACO for reducing irrelevant features. Another correlation based feature selection method with ACO has been reported by Sadeghzadeh and Teshnehlab (2010). Sabeena and Sarojini (2015) also suggested a feature selection scheme based on ACO with its parameters. Jain and Bhadauria (2016) extracted visual features in terms of geometric invariant function. Further, three swarm intelligence algorithms viz. Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Glow Worm Optimization were deployed to yield optimal features. Jaganathan and Vennila (2013) designed a framework of feature dimensionality reduction technique for medical image retrieval system. The feature extraction scheme is carried out with Gray Level Co-occruence Matrix (GLCM), Tamura and Gabor filters. These extracted features are then applied with PSO and ACO to select the most optimal feature sub set. Bhargavi *et al*. (2013) developed an image retrieval system by extracting color and texture features with Color Coherence Vector (CCV) and Gabor Filters. Here instead of ACO, PSO is adopted to classify the optimal features to represent the entire image. Adebisi *et al*. (2015) utilized both GA and ACO for facial feature extraction and selection scheme. The performance analysis of GA and ACO in terms of False Acceptance Rate (FAR), False Rejection Rate (FRR), accuracy and computation time is carried out and the same is also reported. Pal *et al*. (2013) extracted features from faces with wavelet transform and utilized ACO for feature selection scheme in Support Vector Machine (SVM). Babatunde *et al*. (2014) reported a dual level scheme for selecting features as first level corresponds to ACO and the second level with GA as metaheuristic algorithm. Recently an image retrieval system that extracts feature with wavelet is introduced by Rashno *et al*. (2015). These wavelet features are also subjected to ACO for selecting optimal sub set of features for retrieving similar kind of images. The significance of orthogonal polynomials model for low level feature extraction scheme in designing an effective image retrieval system is already found by Krishnamoorthy and Kalpana (2012) and Krishnamoorthi and Bhattacharya (1998).

From the literature survey, it is evident that ACO reduces the feature vector size considerably. But, it is also noted that if the feature extraction scheme works perfectly in extracting the most vital features then the time and space complexity in retrieval systems will be very much reduced. Hence, in this study, a new feature extraction scheme with orthogonal polynomials model and selection scheme with ACO for video retrieval system is proposed.

## MATERIALS AND METHODS

**Mathematical preliminaries for feature extraction from key frames with orthogonal polynomials:** As per the classical definition, the color frame formation can be described as:

$$I(x, y, z) = \iiint f(\xi, \eta, \gamma)\, d\mu(\xi)\, d\mu(\eta)\, d\mu(\gamma) \quad (1)$$

where, the object function f ($\xi$, $\eta$, $\gamma$) is integrable on a measure space and $\mu$ is a $\sigma$ finite measure with an infinite number of points of increase. The image I can be considered to be a signed measure on the ring of all measurable sets. It can be easily shown that if I is non-negative and finite valued on the $\sigma$ ring $\Re$ of measurable sets then f can be defined as a kind of derivative of I relative to a signed measure supported by a null set. Expressing object function f in terms of derivatives of the image function I relative to its spatial and color coordinates is very useful in connection with devising a color image transform coding technique. Since, representation of f in terms of derivatives of I is considered to be an ill-posed problem it is desirable that differentiation of I must undergo a smoothing process. The underlying smoothing operation can be either of the following two types of linear transformation. The integral convolution transformation:

$$f(x) = \int \delta(x-t)\, I(t)dt \quad (2)$$

The ordinary linear transformation:

$$f_i = \sum_{k=0}^{n-1} u_{ik} I_k,\ (i = 0, \ldots, n-1) \quad (3)$$

The linear transformation defined in Eq. 2 by the matrix $|\delta(x_i\text{-}t_j)|$ is a smoothing operation provided it is totally positive whereas the linear transformation defined in Eq. 3 by the matrix U = $|u_{ik}$ is a smoothing operation provided it is totally positive. The matrix U is totally positive provided all the minors of all orders of its determinant $|u_{ik}|$ are non-negative. The point-spread function M(s, x) is considered to be a real valued function defined for (s, x)$\in$S$\times$X where, S and X are ordered subsets of real values. In the case where S consists of a finite set {0, 1, ..., n-1}, the function M(s, x) reduces to a sequence of functions:

$$M(i, x) = u_i(x),\ i = 0, 1, ..., n-1$$

Consequently, the linear three dimensional image transformation can be shown as:

$$\beta'(s, \varsigma, \eta) = \int_{x\in X}\int_{y\in Y}\int_{z\in Z} M(\zeta, x)\, M(\eta, y)\, M(s, z)\, I(x, y, z)\, dxdydz \quad (4)$$

The point-spread function M(s, t) ($M(i, t) = u_i(t)$) is a row, column and color smoothing operation provided the set of functions $\{u_0(t), \ldots, u_{n-1}(t)\}$ is a T-system over a closed interval [a, b]. Considering each of S, X, Y and Z to be finite set of values {0, 1, ..., n-1}, the matrix notation of Eq. 4 is:

$$\left|\beta'_{ijk}\right|_{i, j, K=0}^{n-1} = \left(|M|\otimes|M|\otimes|M|\right)^t |I| \quad (5)$$

where, the point spread operator |M| is:

$$|M| = \begin{vmatrix} u_0(x_0) & u_1(x_0) & \cdots & u_{n-1}(x_0) \\ u_0(x_1) & u_1(x_1) & \cdots & u_{n-1}(x_1) \\ & \vdots & & \\ u_0(x_{n-1}) & u_1(x_{n-1}) & \cdots & u_{n-1}(x_{n-1}) \end{vmatrix} \quad (6)$$

$\otimes$ is the outer product and $|\beta'_{ijk}|$ be the $n^3$ matrices arranged in the dictionary sequence. |I| is the image and $|\beta'_{ijk}|$ be the coefficients of transformation. These, $\beta''_{ijk}$, transformed coefficients obtained with the orthogonal polynomials takes the effect of individual color planes as well as the interactions among the color planes.

We, consider the set of orthogonal polynomials $u_0(x), u_1(x), \ldots, u_{n-1}(x)$ of degrees 0, 1, 2, ..., n-1, respectively. The generating formula for the polynomials is as follows:

$$u_{i+1}(x) = (x-\mu)u_i(x) - b_i(n)u_{i-1}(x) \quad \text{for } i \geq 1, \qquad u_1(x) = x-\mu \text{ and } u_0(x) = 1 \quad (7)$$

Where:

$$b_i(n) = \frac{\langle u_i, u_i\rangle}{\langle u_{i-1}, u_{i-1}\rangle} = \frac{\sum_{t=1}^{n} u_i^2(x)}{\sum_{t=1}^{n} u_{i-1}^2(x)}$$

And:

$$\mu = \frac{1}{n}\sum_{t=1}^{n} x$$

Considering the range of values of t to be $x_i = i$, i = 1, 2, 3, ..., n, we get:

$$b_i(n) = \frac{i^2(n^2-i^2)}{4(4i^2-1)}$$

$$\mu = \frac{1}{n}\sum_{t=1}^{n} t = \frac{n+1}{2}$$

The point-spread operators |M| of different size can be constructed from Eq. 6 for $n\geq 2$ and $t_i = i$. For the convenience of point-spread operations, the elements of |M| are scaled to make them integers as represented in section III and hence the proposed coding involves only integer arithmetic.

In case of R-G-B color space, the elements of the finite set Z for convenience can be labeled as {1, 2, 3}. For the sake of computational simplicity, the finite Cartesian coordinate set S, X and Y are also labeled in the identical manner. The point spread operator in Eq. 5 that defines the linear orthogonal transformation of color images can be obtained as $|M|\otimes|M|\otimes|M|$ in which |M| can be computed and scaled from Eq. 7 as follows:

$$|M| = \begin{vmatrix} u_0(x_0) & u_1(x_0) & u_2(x_0) \\ u_0(x_1) & u_1(x_1) & u_2(x_1) \\ u_0(x_2) & u_1(x_2) & u_2(x_2) \end{vmatrix} = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix} \quad (8)$$

The set of 27 three dimensional polynomial basis operators $O_{ijk}(0\leq i, j, k\leq n-1)$ can be computed as:

$$O_{ijk} = \hat{u}_i \otimes \hat{u}_j \otimes \hat{u}_k$$

where, $\hat{u}_i$ is the $(i+1)^{st}$ column vector of |M|. The operator $O_{ijk}$ is arranged in the dictionary sequence in such a manner that it becomes the $(i\times 3^2+j\times 3+k)+1^{st}$ column vector of the point-spread operator $|M|\otimes|M|\otimes|M|$ in Eq. 5.

**Proposed feature extraction and selection scheme with orthogonal polynomials and ant colony optimization for content based video retrieval system:** The proposed feature extraction and selection schemefor CBVRS with orthogonal polynomials and ACO comprises of four steps namely shot detection key frames identification low level feature extraction feature selection scheme with ant colony optimization and the same is presented in Fig. 1.

At first, the video file is converted in to number of frames that are further subjected to the proposed orthogonal polynomials model to derive transform coefficients. These transformed coefficients are utilized to detect shots and to select representative frames. The representatives (key frames) are again applied with orthogonal polynomials model to extract low level feature such as texture, edge and smooth. Since, extracted features are large in dimension, ACO is adopted to reduce the size and to select optimal features for representing a video key frame. The above steps are discussed in detail in the following sub-sections.

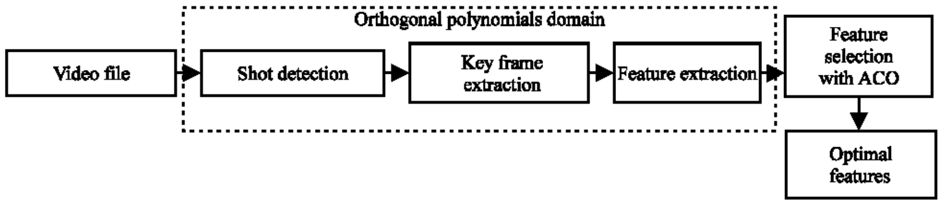


Fig. 1: Block diagram of proposed feature extraction and selection scheme for CBVRS

**Shot detection:** In this research, motion vector analysis is adopted with orthogonal polynomials to detect shots. Initially, each frame is partitioned into n×n matrix blocks termed as macro blocks that are further subjected to orthogonal Polynomials Model to derive Direct Coefficients (DC) and Alternative Coefficients (AC). From these transformed coefficients, only AC values are noted and stored for further investigation. In order to identify the movement, transformed macro block of a current frame $f_c$ is compared with macro block of next frame $f_n$. The matching of one block with another is performed with mean squared error function MSE as given in Eq. 9 which is most computationally less expensive:

$$MSE = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \left[ \left(\beta^{i}_{ij}\right)_{f_c} - \left(\beta'_{ij}\right)_{f_n} \right] \quad (9)$$

Where:

$N$ = The size of macro block

$(\beta^{i}_{ij})_{fc}$ and $(\beta'_{ij})_{fn}$ = The transformed coefficients of current frame and next frame

The macro block that results in the least cost (nearly 0) is the one that matches the closest to current block. This movement calculated for all the macro blocks comprising of an output frame, constitutes the motion estimated in the current frame. This output frame shows motion vector in all directions. Sequences of frames within a shot that fall under the same valid motion class are grouped together into further sub shots according to their motion sequences.

Having detected shots in a video file, the next aim is to identify key frames with in a shot to represent the video. The proposed key frame identification scheme with orthogonal polynomials is described in the next sub-section.

**Key frames identification with DC image formation in orthogonal polynomials:** At first, each frame with in a shot is divided in to (n×n) blocks that are further subjected to orthogonal polynomials model to derive DC and AC coefficients. In this research, leaving AC coefficients, DC coefficients are utilized to form a DC image that is in size of (8×8). Since, the size of DC image is very smaller when compared with the original frame, the computation time is reduced considerably. In order to identify the key frames that are available within a shot, these DC images that are formed with DC coefficients are compared consequently. For instance, let us consider two frames viz. $(f_n)$ and $(f_{n-1})$ of a shot. Now, the frames $(f_n)$ and $(f_{n-1})$ are then applied with orthogonal polynomials model to derive DC coefficients and with the help of these derived coefficients, DC images of size (8×8) say $(DCf_n)$ and for $(f_n)$ and $(f_{n-1})$ are formed. On the obtained DC images, again apply orthogonal polynomials model to derive a single DC value from $(DCf_n)$ and $(DCf_{n-1})$. The extracted DC value of $(DCf_n)$ and $(DCf_{n-1})$ are compared and the frame that has the highest DC value is treated to be a key frame. Having this frame as a reference, consequent frames are compared with DC value and the frame that has the highest value compared with reference frame is also selected as a key frame kf as given in Eq. 10:

$$kf = \max\ DC\left(f_n,\ f_{n-1}\right) \quad (10)$$

As an outcome of this proposed work, key frames are selected to represent the shot. These identified key frames are then subjected to orthogonal polynomials to extract edge, texture and smooth features and the same is described in detail in the next sub-section.

**Low level feature extraction scheme with orthogonal polynomials:** The feature extraction is crucial in designing an effective content based video retrieval system. The extracted features must be significant, compact and fast to compute. Hence, the proposed system extracts low level feature such as color, edge and texture to represent the entire video file. To extract these low level features, it is necessary to partition the image into number of blocks on which the proposed orthogonal polynomials model is applied. Now, the video frames are in transform domain and hence, the coefficients (DC and AC) are utilized to extract the color, edge and texture features. A sample block of key frame from which the features are extracted is given in Fig. 2. Figure 2, the upper left represents DC value and in this research, it is modeled to be color feature. The alphabets A, B, C, D, H and L

| | A | B | C |
|---|---|---|---|
| D | E | F | G |
| H | I | J | K |
| L | M | N | O |

Fig. 2: Sample block of key frame

represents edge feature and I, J, M and N represents texture information. By this way for all the blocks of a key frame, the feature extraction process is carried out.

The significant orthogonal polynomials coefficients that represent color, edge and texture for a single block is stored in $c_f$, $c_e$, $c_t$ and the same is given in Eq. 11:

$$\begin{aligned} c_f &= \beta'_{000},\ e_f = \beta'_{001},\ \beta'_{002},\ \beta'_{003},\ \beta'_{100},\ \beta'_{200},\ \beta'_{300} \\ t_f &= \beta'_{211}, \beta'_{212}, \beta'_{311}, \beta'_{312} \end{aligned} \quad (11)$$

On the whole for a single block of a key frame, the proposed work extracts exactly 11 feature values that include one color, six edge and four texture values. Hence, the overall features, i.e., extracted are larger in dimension and hence there is a need of a feature selection scheme to select optimal features. The selection of optimal features with ACO is presented in the following sub-section.

**Proposed feature selection technique with ant colony optimization:** Having extracted the low level color, edge and texture features from a key frame, now the proposed system focuses on removing both irrelevant and redundant with ant colony optimization.The steps involved in ACO are initialize parameters selection of attribute heuristic value calculation fitness function and pheromone updating and the same is given in Fig. 3.

**Initialization of pheromone values:** Generally, the pheromone value is generated with random numbers. In this research, it is modeled to be like, the first ant will never prefer any attribute and hence the initial pheromone is calculated as given in Eq. 12:

$$\upsilon_{ij} = \frac{1}{N} \quad (12)$$

Where:
ij = Nodes
N = The total number of attributes present

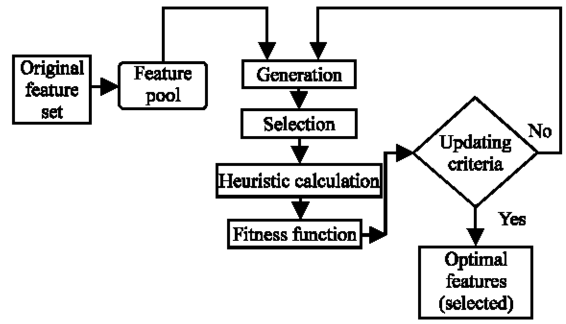


Fig. 3: Steps involved in feature selection scheme with ACO

**Selection of attribute:** An ant uses two components to calculate the probability of moving from the present node to the next node. The first component identifies the amount of pheromone between node i and node j and the second component is a heuristics value that represents the worth of a node. The probability of choosing the next node as node j after arriving i node is given in Eq. 13:

$$p_{ij} = \frac{[\upsilon_{ij}]^{\alpha} \times [\eta_{ij}]^{\beta}}{\sum_{k \in S} [\upsilon_{ij}]^{\alpha} \times [\eta_{ij}]^{\beta}} \quad (13)$$

Where:
$\upsilon_{ij}$ = The pheromone value associated with node i and j
$\eta_{ij}$ = The value of heuristic function

The special parameters influence the pheromone and heuristic values.

**Heuristic value calculation:** In this research, ant is modeled to make decision about the next node with heuristic value. At first, the entropy of target attribute is calculated. Now, the average conditional entropy is calculated for each attribute and subtracted from target attribute entropy value and termed as information gain, i.e., given in Eq. 14:

$$\text{Gain}(S, A) = \text{Entropy}(S) - \sum_{v \in V} \frac{S_v}{S} \text{Entropy}(S_v) \quad (14)$$

Where:
V = The set of all possible Values of attribute
A and $S_v$ = The sub set of samples of S
V = The value of V
S = The number of Samples

**Fitness function:** Fitness function plays a significant role in finding out with a worst set of features. In this research, each feature is evaluated based on the following fitness function as given in Eq. 15:

$$\text{FitVal} = \frac{(\text{pos})\times(\text{fv})}{(\text{tnof})\times(\text{Noc})}\times \text{w} \tag{15}$$

Where:

pos = The current position of the feature value
fv = The feature value
tnof = The total number of features
Noc = The Number of occurrences
w = The constant weighting parameter

The threshold ($T_a$) is computed adaptively based on fixed location of the population as given in Eq. 16:

$$T_a = \frac{\sum_{i=0}^{n} \text{FitVal}}{\text{tnof}} \tag{16}$$

Where:

FitVal = The Fitness Value of each feature
tnof = The total number of features on fixed location

**Pheromone updating:** The pheromone is updated only if the ant completes tour so that the future ants can make use of this information for their search. The amount of pheromone on each link occurring in the current feature sub set selected by ant is updated according to Eq. 17:

$$\upsilon_{ij}(t+1) = (1\text{-p})\times\upsilon_{ij}(t)+\left(1\text{-}\frac{1}{\text{FitVal}}\right)\upsilon_{ij}(t) \tag{17}$$

where,$\upsilon$ is the pheromone value between node i and node j in current iteration and p represents the pheromone evaporation rate and fitness is the quality of the current path constructed by ant. The pheromone update is done by reducing the old pheromone value and by increasing it in proportion to select the best features Algorithm 1.

**Algorithm 1; Algorithm of proposed feature selection technique with ACO:**

Input: Feature values of key frame
Output: Selected (Optimal) feature values
Step 1: Input the key frame
Step 2: Calculate heuristic value of each attribute with information gain
Step 3: Generate population for ants
Step 4: Initialize parameters for ACO
Step 5 : FOR each ant, generate sub set s
Step 6 : Evaluate each sub set s
Step 7 : IF the current fitness is better than previous one, then treat the current as Optimal and end if
Step 8: Update the pheromone value
Step 9: Repeat until stop criteria does not meet
Step10: end for
Step11: Form the best feature subset
Step12: End

As an outcome of this algorithm, the best sub set of features are selected for each key frame in a video file and stored in feature library for content-based video retrieval system.

## RESULTS AND DISCUSSION

The proposed research is implemented in Java and experiments were carried out on Pentium 4 3GHz personal computer installed with 3GB RAM running on Windows 8 (32 bit version). The proposed feature extraction and selection scheme in orthogonal polynomials transform domain with ACO has been experimented with four categories of standard videos. The details of test videos with total number of frames are presented in Table 1.

Sample frames of cricket video that are of size (360×240) with pixel values in the range are shown in Fig. 4. The proposed system first detects shot the input frames are partitioned in to (3×3) blocks and applied with orthogonal polynomials transformation to yield DC (Direct Coefficients) and Alternate Coefficients (AC) values. Leaving DC values, the AC values are alone considered and each macro block of current and previous frame are compared with respect to Mean Squared Error (MSE) value. By identifiying the movement in this research, it is modeled to detect a shot where significant changes occur. The results of the proposed shot detection technique for cricket video file is presented in Fig. 5.

Having detected the shots in cricket video, the next step in this proposed research is to identify key frames to represent each shot. Since, all the frames with in a shot is almost similar, the proposed scheme generates DC images with the help of DC coefficients that are already stored. DC images of consecutive video frames are then compared and the image that possesses maximum DC values is treated to be a key frame in this research. The results of the proposed key frame identification scheme with DC image formation in orthogonal polynomials transform domain for the video frames shown in Fig. 4 is presented in Fig. 6.

From the identified key frames of a shot, low level features viz. edge and texture are extracted with the proposed orthogonal polynomials model. Each key frame is divided into (4×4) blocks that are subjected to derive transformed coefficients. The proposed feature extraction scheme utilizes only few of the orthogonal transform coefficients in horizontal, vertical and diagonal directions for extracting color, edge and texture features. For each block of a key frame, one coefficient for color feature, six coefficients for edge and four coefficients for texture are


Fig. 4: Sample frames of cricket video


Fig. 5: Results of the proposed shot detection technique with orthogonal polynomials model for the video frames shown in Fig. 4

Table 1: Details of test videos

| Video type | No. of frames |
|---|---|
| Cricket | 1952 |
| Animation | 3248 |
| News 1 | 8097 |
| News 2 | 4194 |

utilized. On the whole, the proposed feature extraction scheme, utilizes eleven coefficients for a block in a key frame. The sample color edge and color texture values of a block for key frame show in Fig. 6 are presented in Table 2.

Each feature in the feature vector with respect to entropy is computed. Based on the entropy value and ACO, the irrelevant features are eliminated one at a time and first 25 top ranked texture features are selected and placed. As mentioned in Table 2, the first 50 top ranked features are selected from edge feature vector. As a result of this scheme, the proposed work finds a feature set of dimension 75. This dimension 75 is obtained after rigorous experimentation and a sample result of feature selection technique for the extracted features shown in Table 2 is presented in Table 3.

Fig. 6: Results of proposed key frame identification scheme for the video frames shown in Fig. 5

Table 2: Sample edge and texture values of a block for a sample video key frame

| Texture representation | Edge representation |
|---|---|
| 3 | -725 |
| 33 | 725 |
| 6 | -636 |
| 7 | 636 |
| 32 | 715.5 |
| 64 | -81.3 |
| 4 | -159 |
| 34 | 159 |
| 35 | -79.5 |
| 36 | 79.5 |
| 63 | -318 |
| 55 | 1431 |
| 53 | -318 |
| 61 | 146 |
| 69 | -146 |
| 101 | 647.3 |
| 167 | . |
| 109 | . |
| 119 | . |
| 117 | . |
| 111 | . |
| 127 | . |
| 103 | . |
| 175 | . |
| 179 | . |
| . | . |
| . | . |

Table 3: Sample result of the proposed feature selection process

| Levels | Selection of features |
|---|---|
| **First level** | |
| 109 | 635.845 |
| 111 | 635.860 |
| 151 | 636.047 |
| 167 | 636.052 |
| 183 | 636.111 |
| 191 | 636.165 |
| 231 | 636.502 |
| **Second level** | |
| 109 | 634.393 |
| 111 | 634.414 |
| 151 | 634.745 |
| 167 | 634.826 |
| 183 | 634.951 |
| 191 | 635.044 |

Selected feature from 1st level: 231, Selected feature from 2nd level 191, 231

The performance of proposed feature extraction and selection scheme for CBVRS is evaluated by conducting experiments on different types of video frames in terms of computation time (msec) at each stage viz. shot detection, key frame identification, feature extraction and selection.

Table 4: Categories of video files

| | Computation time (msec) | | |
|---|---|---|---|
| Video type | Shot detection | Key frames identification | Feature extraction and selection |
| Cricket | 240.09 | 90.32 | 158.42 |
| Animation | 201.72 | 86.87 | 144.60 |
| News 1 | 358.48 | 109.11 | 413.81 |
| News 2 | 296.70 | 97.36 | 265.07 |

For example, for the frames of cricket video shown in Fig. 6, the proposed system consumes 240.09, 90.32 and 158.42 msec, respectively. Likewise, the performance of proposed scheme in terms of computation time (msec) for all the four categories of video file shown in Table 1 is calculated and presented in Table 4.

## CONCLUSION

In this study, a new feature extraction scheme in orthogonal polynomials domain and selection with ACO for CBVRS is presented. Since, all the steps of CBVRS are carried out in the same orthogonal polynomials domain, the computation time is highly reduced. In addition to that ACO is adopted for selecting optimal features and the results obtained are satisfactory. The time taken for each stage is computed which seems to be highly commendable that is highly required for designing a retrieval system.

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