Geometrical Coding For Medical Image Retrieval Using Transformed Contour Coding

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Abstract
In the approach of geometrical coding, curvature based coding are predominantly been used. As in various applications the processing data are large in count or large in representation and the available resources are very lower in count. In such resource constraint environment, the processing efficiency is decreased to very low level specially with processing delay factor. The current retrieval system is observed to achieve the estimation accuracy with the cost of higher computation or the vice versa. With the current demand these algorithms are to be enhanced with various approaches exploiting the representing feature to be simpler and descriptive for ease of searching. A new coding approach using empirical mode decomposition for shape feature descriptor is proposed called linear curvature Empirical coding. The proposed approach of Shape-Depth coding and LCEC results in minimization of processing overhead and presents an improvement in coding efficiency in terms of computation time, recall rate, precision, and processing overhead.

Keyword: contour coding, geometrical coding, 1-D transformation, spectral coding

Introduction
Automation of image coding has resulted in faster and accurate information retrieval in various practical applications. In the process of image coding, wherein image information are coded to represent into an informative detail and then processed to obtain the best match information is called as image retrieval system. In various practical applications, such as medical image processing, trademark processing, ecological and biological learning, metrological and astronomical applications, military application etc., image retrieval systems are in usage or they are in the process of integration to make the operation faster and more efficient. Wherein image retrieval systems are been developing for integration modeling, the concern of processing overhead is large. As in various applications the processing data are large in count or large in representation and the available resources are very lower in count. In such resource constraint environment, the processing efficiency is decreased to very low level specially with processing delay factor. The current retrieval system is observed to achieve the estimation accuracy with the cost of higher computation or the vice versa. With the current demand these algorithms are to be enhanced with various approaches exploiting the representing feature to be simpler and descriptive for ease of searching. Advances in signal processing and applied mathematics have enabled researchers to develop sophisticated techniques to research the geometric content of images. Though such strategies are effective in capturing low-level image features, the gap between these low-level features and high-level representation is still to be merged. The retrieval of image using generic image features such as shape has become progressively vital due to the convenience of representation as an efficient descriptor. These features are dominantly been used in current image retrieval system. Various methods were developed in past to achieve the objective of faster retrieval with better accuracy in topological representation. The very basic representation of such topological coding is the edge based coding, where images are processed to derive outer bounding regions to represent shape. However, edge processing results in large edge coefficients, as they are been extracted with all the information’s crossing threshold limits. This results in large feature coefficients. To achieve lower feature representation with accuracy, contour coding were more preferred. Due to the accuracy of this coding for deriving bounding region leads to its usage more accurately in practical usage. However the issue of non-homogenous pixel distribution, results in discontinuous region detection, which leads to open contour regions. Hence these systems are lower in representation and larger in count. In regard to optimize the process, a scale space projection for curvature representation was also developed. The curvature scale space coding (CSS) is the most effective coding in this domain. CSS based coding is more effective in shape description, due to its inherent property of both noise filtration and shape representation simultaneously. However, the approach of such coding is observed to be limited under spatial similar samples, wherein low varying curvatures also reflects important curvature features for a test sample. Such low varying information’s are neglected in CSS considering as noise. It was hence required to develop new approach to select features from both high and
Shape retrieval system

Several classification methods are available. The most common and general classification is based on the use of shape boundary. The resulting classes are known as boundary and global. Shape representation techniques can also be distinguished between space domain and feature domain. Methods in space domain match shapes on point (or point feature) basis, while feature domain techniques match shapes on feature (vector) basis. The classification of shape representation techniques is shown in figure 1.

![Figure 1: Classification of shape representation techniques](image)

The variety of shape representation techniques are mentioned in the literature. These are mainly classified into contour-based methods and region-based methods. In contour based methods shape features are extracted from contour only. However, in region based the shape features are extracted from the whole shape region. Under each class, these methods are further distinguished between structural and global based on whether the shape is represented as a whole or represented by sub-parts (primitives). It is possible to further separate the different methods under the second hierarchy into feature domain and space domain based on whether shape is represented by points (or point features) or feature vector. Region based methods are general methods which can be applied to generic shapes. Region shape description is another important shape technique in shape modeling family. It is a more general shape description technique than the contour method. Three important and widely used region shape descriptors are comprehensively studied and evaluated in [7]. These descriptors are Geometric Moment Descriptor (GMD), Zernike Moment Descriptor (ZMD) and Grid Descriptor (GD). Their advantages and disadvantages for image retrieval are identified. Their effectiveness and efficiency for image retrieval are comprehensively evaluated. The grid shape descriptor has been extended for general shape description, while previously it has only been applied to contour shape description.

Image retrieval system

Interest in the area of digital image processing has increased n-folds over the past few years. Images can be stored remotely and users in many professional fields are exploiting the opportunities offered to access and manipulate these images in exciting ways. However, they are also discovering that the process of locating a desired image in a large and varied collection can be a source of considerable frustration. To
locate the desired images correctly the researchers are analyzing the widely known problems of image processing. Searching for a solution to the image processing problem is an active area of research in image processing domain. Significant improvement in processing technology in recent year coupled with the decrease in the cost of memory and storage has played a major role in the development of large data base systems. This explosion of stored data has rapidly created the need of new suitable tool to enable the user to manage and retrieve efficiently specific type of the information. For retrieving the images from a large database various image representation and coding techniques were developed. Image recognition is useful in various new applications such as medicine, crime detection, historical research, architecture design, publishing and advertising etc.

With development of the new technologies images are now captured at very high resolutions, and each detail of the image could be extracted at finer level. The contents of the image such as shape, color and textures can be extracted and used as feature descriptors to describe the image. So, the performance of an image retrieval system mainly depends on the efficient representation of the features. Among all these descriptive features, shape is considered as a simpler and distinct feature. Image database are becoming more pervasive due to tremendous growth of digital images, increased availability of inexpensive storage media and widespread use of internet facilities. In many areas of commerce, government, academic and hospitals large collections of digital images are created. Digital image databases open the way to content based searching and thus the development of Content Based Image Retrieval (CBIR) system. Various techniques for storing, browsing, retrieving images have been explored in recent years. The traditional approach to image retrieval is to annotate image by text and then use text based data base management system to perform image retrieval. Here each image is phrased by a keyword. There are several drawback of the text based approach. To specify a keyword for representing large database images is tedious and difficult task for the humans. To overcome the drawbacks of the text based image retrieval system, several coding methods were developed in past to retrieve images. These approaches uses content of an image sample and termed as CBIR system. Lot of research has been carried out on how to retrieve an image using CBIR in the past decade. For a given query image the CBIR system can return group of similar images. CBIR uses the low level features of the image such as color, shape and texture. By extracting these features CBIR system can distinguish and retrieve the images. Below figure 2 shows basic operational architecture for CBIR system.

CBIR carries out the retrieval task in two operational phases as training and testing. In training phase features for all the training samples are extracted and stored in a feature data base. In testing phase for a given query samples same features are extracted and given to the classifier. Classifier compares the features of query image with the features of all the database images. Based on the similarity index the similar images are sent to the output. As more digitized images are collected search for solutions to solve these problems is an increasingly active area for research and development.

With the development of the new technologies the numbers of multimedia computers are increased and networks became more predominant. Large on-line databases (collections) of images and video are becoming more and more popular. From these stored databases there is need for retrieving specific images. Existing technologies are still primitive and it is necessary to develop a user-friendly image retrieval system. Querying by image content is a way to retrieve images based on their content. This method is called QBIC, and a system using QBIC is called a CBIR system. Multimedia information has invaded lot of fields such as weather forecasting, surveillance, criminal investigation, biomedical imaging scientific experiments and so on. However, the technology is not fully developed to be used on a large scale for diverse applications. By means of CBIR searching is one of the most burning issues in the fields of multimedia computing. Human perception is not understood well by machine to automate the retrieval process. Multimedia database are very big in size, so we cannot go for the exhaustive searching of images from these data base. Two important issues in designing CBIR system are accuracy and efficiency. Main goal of this work is to design a system for content-based image searching for 3D as well as 2D images using shape feature. The developed system need to be accurate and robust with respect to changes in scale, rotation and noise.

**Contour Shape Descriptors**

Contour-based shape description is an important shape technique. Contour-based shape descriptors usually involve less computation and storage than region-based shape descriptors. Contour-based shape description can be conveniently applied to applications where shape contours are available. In literature, contour-based shape methods are more popular than region-based shape methods, due to their simple implementation and clear properties. Contour-based shape description has been successfully applied to many applications, such as object recognition, shape coding, character recognition. Contour shape description is an important shape technique. Many contour shape techniques are available. The research implements, evaluates and compares two important and promising contour shape descriptors, they are Fourier descriptor (FD) and curvature.

![Basic model of CBIR system](image-url)
scale space descriptor (CSSD). Previously, there is no comprehensive study and comparison of these two shapes Image Content Color Combined features Texture Shape Text Category Keywords descriptors. The advantages and disadvantages of these two techniques for image retrieval are thoroughly analyzed. Their effectiveness and efficiency for image retrieval are quantitatively evaluated. The purpose of the study is to evaluate the suitability of FD and CSSD for image retrieval. FD is a convenient shape descriptor and there are a number of FD methods. Scale space method has been shown very useful in shape analysis since Asada and Brady used it to derive a primal sketch from a shape. Its use for shape retrieval has been proposed. In this section, CSSD is described and studied in details. Basically CSS method treats shape boundary as a 1-D signal and analyze this 1-D signal in scale space by examining zero crossings of curvature at different scale, the concavities/convexities of shape contour are found. These concavities/convexities are useful for shape description because they represent perceptual features of shape contour. CSS descriptors are essentially the descriptors of key local shape features. By dealing shape in scale space, not only the locations of, but also the degree of convexities (or concavities) of shape boundaries are detected. How fast a planar contour is turning can be measured by the curvature. The CSS descriptors can be built by first calculating the CSS contour map. This map is a multi-scale organization of the curvature zero-crossing points. A digital image consists of group of pixels arranged in matrix. Simplest mode of image representation is by using shape feature. To describe the shape of an image edges play very important role. Edge operators derive coefficients out of the bounding regions in many image representation techniques. For many years the fundamental issue in image processing was detecting the edge of an image. Computer vision researchers are trying to design good edge detectors, since edge detection is an essential step in many computer vision applications. A standard approach defines a 1-D edge operator. This operator is then extended to the 2-D. Step edges are the most useful image intensity structures. Step edges are dominantly used in the detection. There are various forms of 1-D step edge operations investigated and one such approach is defined by Canny [5, 8]. This approach performs a more systematic investigation to find an optimal edge by incorporating an explicit localization criterion and a detection criterion (SNR). To find an optimal edge this approach presents a numerical solution using three criteria: higher SNR, more accurate localization, and fewer peaks in the response function. This method describes the use of the first derivative of a Gaussian function as a good approximation for implementation.

Contour Evolution

Contour of an image can be obtained from an edge. For the detection of contour all the real corners must be detected. The system should avoid detecting the false corners. The contour evaluator must be effective in finding the true edges. For finding the contour, 8-region neighborhood-growing algorithm is used. In this algorithm following estimation process was used:

**Algorithm 8 region neighborhood-growing Contour**

1. Read image from image database
2. Apply preprocessing on images.
3. For the image determine edge feature by applying Canny edge operator
4. Find the initial pixel by vertical or horizontal scanning of the edge image.
5. Take the initial pixel as reference and call it as seed pixel.
6. Find the next pixel use eight adjacent neighbors taking seed pixel as starting co-ordinate.
7. For the obtained seed, its coordinate (x, y) is derived, and a scanning is carried out in order of (1, 2, 3, 4, -1, -2, -3, -4) as shown in figure 3. 3, defined by its coordinates as, [(x+1, y), (x+1, y+1), (x, y+1), (x-1, y+1), (x-1, y), (x-1, y-1), (x, y-1), (x+1, y-1)] directions.
8. A high value of the leading edge is traced, and the direction in which this coordinate is found is updated as new seed coordinate.
9. With the updated seed coordinate the tracings is repeated, until the Seed initial is met.
10. The traced path in this process then formulates a bound contour, which is then used for feature description.

The process of orientation pattern for contour evolution is shown in above figure 2 and the process of contour evolution is depicted in below figure 3.

![Figure 3: Tracing operation in contour evolution.](image_url)
8-point connectivity technique is applied to find Shape signature. This is a one dimensional representation of the shape, which is obtained by applying on the 2D closed edge region. As engineering/ CAD objects have well defined centroid \((x_c, y_c)\) and also retrieval has shown to be better with central distance, is used as a shape representation. The feature vector representing the central distance between point on the contour \((x, y)\) and the centroid \((x_c, y_c)\) is given by:

\[
V_c=(x-x_c, y-y_c, 0)
\]

Where,

\[
x_c=\frac{1}{N}\sum_{i=0}^{N-1}(x_i)
\]

and

\[
y_c=\frac{1}{N}\sum_{i=0}^{N-1}(y_i)
\]

Where, \(N\) is the total number of pixels.

For the feature extraction, a new empirical based coding, to retrieve geometrical feature information’s is proposed. This method uses edge descriptors. Edge descriptors represent the image information in two logical levels. One high and other low based on the bounding regions pixel magnitude. Edge information’s are used to derive the regions content form which feature extraction can be carried out. In edge based coding the discontinuous in edge regions reflects in discarding of image regions and insertion of edge increases the number of processing regions. So, this results in increased overhead for the feature extraction and number of feature coefficients. By doing this retrieval performance is reduced. To overcome the Limitations of region selection on edge coding curvature based coding are proposed. This approach is considered to be more effective in region extraction based on the closed bounding regions, termed as contours. The approach of contour based curvature coding is also applied for the image retrieval applications.

**Edge coding and Contour coding**

An edge based method to extract the shape features is considered to be a prominent method for retrieving the images from the database. Moon H in [5] has proposed an ideal method for shape detection using edge based method. This method proposes derivative of the double exponential (DODE) function. 2-D shapes can be accurately detected using this approach. Step function is used to model the shape boundary. 1-D optimal step edge operator is derived first in this approach. This operator minimizes the noise power and the mean squared error between the input and the output filter. This approach is considered as an enhanced modeling of image shape representation. Exact shape of an image can be derived by using DODE filter which is applied over the bounding contour. An operator is defined for shape detection by extending the DODE filter along the shape’s boundary contour. To estimate the possibility of the presence of the given shape the responses are accumulated at the centroid of the operator. This method of detecting a shape is in fact a natural extension of the task of edge detection at the pixel level to the problem of global contour detection. By using this simple filtering scheme systematic analysis of edge-based shape detection can be done. The number of feature vectors defined for edge based methods are more. To overcome this contour based approaches are developed. In addition to the edge and contour based coding various other approaches such as in [7] a graph structure, named as concavity graph is proposed. This approach represents multi object images using individual objects and their spatial relationships. Shape context (SC) [8] is another method which uses a histogram based modeling for efficient shape description. In [9] a polar transformation uses the shape points about the geometric center of the object. The distinctive vertices of the shape are extracted and used as comparative parameters to minimize the difference of shape distance from the center. Based on local perceptual shape descriptor and similarity indexing a retrieval method is proposed in [6]. A local invariant feature called ‘SIFT’ (Scale-invariant feature transform) is proposed in [6]. This method computes a histogram of local oriented gradients around the feature point. However, the contour based or the other techniques such as graph based, context based etc. defines the overall bounding contour. But, the feature coefficients are very large in these methods. Large feature data set is built by projection in the contour region which is taken as a feature.

**Curvature Scale Space (CSS) Coding**

To reduce the large feature vectors, curvature coding has emerged. A curvature based scale space representation is described in [2]. Rich information about the object can be found in a closed boundary curve. The object shape and often type of object can be recognized using the curve. Rate of change of slope in continuous case is defined as the curvature. In discrete space, the curvature description needs to be slightly modified. This modification is to overcome difficulties resulting from violation of curve smoothness. The curvature scalar descriptor (also called boundary straightness) finds the ratio of the total number of boundary pixels (length) to the number of boundary pixels where the boundary direction changes significantly. The boundary will be straighter if the total number of direction changes is minimal. In this system the samples are preprocessed for filtration and dimensional uniformity in the preprocessing stage. The preprocessed samples were further processing. The accuracy of these feature descriptors defines the processing accuracy of the system. The retrieval system based on a CSS feature descriptor is as illustrated below in figure 4.

**Database:**

Figure 4: Conventional CSS based recognition system
Local shape features are defined by CSS descriptors. As the shape is considered in scale space, we can detect locations along with the degree of convexities (or concavities) of shape boundaries. Curvature is an important local measure to find how fast a planner contour is turning. To obtain the CSS descriptors first we must calculate the CSS contour map, SYM-scale organization of the curvature zero crossing points are known as CSS contour map. For calculating the curvature is derived from shape boundary points. Curvature zero crossing points are then located in the shape boundary. The shape is then evolved into next scale by applying Gaussian smoothing, which uses the convolution operation of varying values of sigma. As the sigma increases, the evolving shape converts with the smoother and smoother boundary. New curvature zero-crossing points are located at new scale and this process continues until no curvature zero crossing points are found. The final CSS contour map consists of all zero crossing points (i, σ). Where i is the location and σ is the scale at which zero cross is obtained. The maxima of CSS contour map (only those peaks higher than the threshold) are not readily available and needs to be extracted. These maxima’s are sorted in descending order and stored in database as CSS descriptors. The basic properties of the CSS representation [7], which makes it almost unique for shape similarity retrieval, are as follows:

- **CSS descriptor** is translation, scale and rotation invariant.
- It is robust with respect to noise, since sigma value is selected above some threshold and peak value of the noise is far below than the selected sigma.
- It retains the local information of the input shape. Every concavity or convexity on the shape has its own corresponding contour on the CSS image. Each point in horizontal axis of CSS image has its corresponding on the actual boundary.
- It is fast. In response to a query, the system computes the CSS image of the input boundary and extracts its maxima. The system then compares the extracted feature vector with images from the database. Both the feature extraction and matching process are fast.
- It is reliable. The results confirm the reliability of the representation and matching algorithm.

To find the CSS image first step is the preprocessing. x and y coordinates represents the boundary point for an image. The total points vary from 400 to 600 for sample images in our database [8]. All the samples of the database are resampled with the boundary and arc length is represented by 300 equally distant points as a normalization process. Therefore, perimeter of all boundaries will now become same. To find the CSS image first step is preprocessing. After the preprocessing stage find edge of an image. This is obtained using canny edge detector as discussed in section 3. Next step is to generate the contour and contour is generated by following the steps as discussed in section 3. On the obtained contour coordinates (x(u), y(u)) a curvature coding is applied. By defining dominant curve regions this coding is used to extract the shape features. The curvature, ‘K’, for given contour coordinates can be defined as [7]:

\[
k(u) = \frac{x'(u) * y''(u) - y'(u) * x''(u)}{[(x'(u))^2 + (y'(u))^2]^{3/2}}
\]

Where \((x', y')\) are first derivative and \((x'', y'')\) are the double derivative of x and y contour co-ordinates respectively. This represents the curvature pattern for the extracted contour. A smoothing of such contour reveals in the dominant curvature patterns, which illustrates the representing shape of the region. Hence to extract the dominant curvature patterns, the obtained curvature is recursively smoothed by using Gaussian smoothing parameter (σ). The Gaussian smoothing operation is then defined by,

\[
X(u, σ) = x(u) ⊗ g(u, σ) \quad Y(u, σ) = y(u) ⊗ g(u, σ)
\]

Where, \(g(u, σ)\) denotes a Gaussian of width ‘σ’ defined by,

\[
g(u, σ) = \frac{1}{σ\sqrt{2π}} e^{-\frac{u^2}{2σ^2}}
\]

The curvature ‘K’ is then defined as;

\[
k(u, σ) = \frac{X_u(u, σ)Y_{uu}(u, σ) - X_{uu}(u, σ)Y_u(u, σ)}{(X_u(u, σ))^2 + (Y_u(u, σ))^2}
\]

Figure 5 shows the process of smoothening and the application of smoothening factor ‘σ’.

The similarity among two shapes is measured by the sum of the peak differences between all the matched and unmatched peaks. The powerfulness of CSS descriptors owes to its ability to capture those key local features such as locations and degree of convexity (concavity) of the curve segments on the shape boundary. These features reflect human perception in analyzing the similarity between the two shapes. The number of feature vectors for CSS descriptors are very less and the representation is robust due to Gaussian smoothing process. CSS images are robust with respect to scale, noise and orientation. A rotation of the object usually causes a circular shift of its representation, which is easily determined during the matching process. The effect of a change in the starting point is also the same. Due to normalization, scaling does not change. Noise adds some small contours to CSS image, but the main contours still remains unaffected. The CSS matching is done by extracting maxima of CSS Contours. Each image in the database is represented with the locations of its CSS contour maxima. For example, the representation for the object in figure 5 is given as:

Maxima Extraction = \{(82 7.75), (144 7.5), (210 7.25), (279 7.25)\}

For eliminating the noise just maxima which are higher than 0.2 the largest σ of the CSS image are considered. The locations of the maxima must be extracted from the CSS image. A CSS contour is normally connected except in a neighborhood of its maxima. Combination of wavelet transform and Fourier descriptors can be used as an efficient
descriptor as proposed by L. Kuntuu [7]. Fourier descriptors are specified in multiple scales. Complex wavelet transform is used to specify the boundary function of the object. Now, the Fourier transformation is applied to wavelet coefficients in multiple scales. It is also called multi scale convexity concavity (CSS) representation. Here, different scales are obtained by smoothing the boundary with the Gaussian kernels of different widths. The curvature relative displacement of a contour point with respect to its position in the preceding scale level is measured with respect to the boundary point. An improvement to this is presented by Mark Nixon in [5]. Here, the image is represented in 2D space and boundary and exterior parts of the objects are used more than the central part. It also uses the High pass Gaussian filter and polar transformation.

A) Issues in Existing CSS Based approaches

The curvature coding approach results in lower feature descriptors for an image retrieval system. However, in these coding, features are extracted based on a thresholding of the curvature plot and values with higher magnitude are selected. These approaches rejects the lower variational information considering as noise in feature selection process. However, in various image samples curvature with variations also exists for a longer time period. So, this assumption which discards completely the lower information in image feature selection process reduces the ability of the descriptive features which are used in image retrieval process.

![Figure 5: Smoothening process for a curvature at different values of sigma.](image)

For example, for a given CSS plot for a query sample, the region below the threshold is considered to be non-informative and totally neglected. This consideration leads to following observations;

1. Under semantic objects having similar edge representation, a false classification will appear.
2. Information’s at lower regions also reveals information of images having shorter projections such as spines.
3. Direct elimination of the entire coefficient leads to information loss as well, a random pickup will leads to higher noise density.

These problems need to be overcome to achieve higher level of retrieval accuracy in temporal semantic samples, or with sample having finner edge regions. To achieve the objective of efficient retrieval in semantic observations, a linear curvature Empirical coding (LCEC) is proposed. The proposed approach is as outlined in following section.

**Operational Description**

This approach present to curvature coding based on 8-neighborhood region growing method for contour extraction and region representation as described in section 3. To extract the curvature points in this approach a CSS coding is defined as discussed in section 3. These curvatures are stored as a measuring parameter defining, shape of the image. A CSS explores the dominant edge regions in an image, wherein curvature having higher dominance will be presented for a longer time than the finer edge regions. A thresholding approach is then applied over this CSS curve to pick the defining features, and edge coefficients which are extracted over the threshold are used as feature descriptor. Below figure 6 demonstrates a CSS plot and the process of feature selection. A CSS representation of a given query sample is illustrated in figure 6. (p1,k1),(p2,k2),… (pn,kn) are the extracted feature values used as image descriptor. However, in such a coding process, information’s lower than the threshold is totally neglected. This elimination is made based on the assumption that, only dominant edges exist for longer duration of smoothing and all the lower values are neglected treating it as a noise. To overcome this we have proposed a novel LCEC approach. In this approach by the linearization of curvature coding and normalization process is proposed. The linearization process converts the curvature information into a 1-D plane. The resultant information is then processed for extracting the features based on Empirical coding. This suggested method improves the selection of feature relevancy, in terms of selectivity. Since, now features are selected based on variational density rather than magnitudes.

C) LCEC Based Retrieval System

It could be observed that the obtained CSS plot represents the edge variations over different smoothing factors. This CSS representation looks like a 1-D signal with random variations. Considering this observation, a linear representation of the curvature coding for feature representation is proposed. For the linearization of the CSS curve, a linear sum of the entire curvature plane at different Gaussian smoothing factor is taken. The linear transformation is defined as,

\[
L_s = \sum_{i=1}^{n} K_i(u, \sigma)
\]

Where, \(L_s\) is the linearized signal, and \(K_i\) is the obtained curvature for \(i^{th}\) value of \(\sigma\).

A linearized signal representation for a CSS plot is as shown in figure 7. This signal represents all the variations present from the lower smoothing to the highest smoothing factor. Among all these variations, there is need to extract the required variation coefficient, which best represent the image shape. To extract the optimal peak points, an empirical coding is developed.

![Figure 6: CSS plot and process of thresholding](image)
Figure 7: Linearized representation of a CSS plot

Algorithm
Input: linear curvature, \( x[n] \)
Output: Feature vector \( s_i \)
Step 1: Perform DWT computation for the obtained linear curvature signal.
For DWT computation:
Step a: compute the Local maxima (\( X_{\text{max}} \)) and local minima (\( X_{\text{min}} \)) for linear curvature sequence \( x[n] \)
Step b: compute minimum and maximum envelop signal, \( e_{\text{min}} \) and \( e_{\text{max}} \).
Step c: Derive the mean envelop \( m[n] \).
Step d: Compute the detail signal \( d[n] \).
Step e: Validate for Zero mean stopping criterion.
Step f: Buffer data as BAND or residuals, from the derived detail signal.
Step 2: For obtained Db compute spectral density of each BAND using PSD.
Step 3: Select two Db having highest energy density (\( I_1, I_2 \)).
Step 4: Compute threshold limit for \( I_1, I_2 \) as 0.6 of max (\( I_i \)).
Step 5: Derive the feature vectors \( (s_i) \) from these two Db for classification.

The operational flow chart for the proposed LCEC approach is summarized in figure 8.

Feature Extraction
The obtained Db \( \{I_1 - I_7\} \) are the decomposed detail Db reveling different frequency content at each level. At each decomposition level the residual BAND, \( r[n] \), is decomposed in each successive BAND to obtain finer frequency information’s. Each obtained BAND, reveals a finer frequency content and based on the density of these frequency contents, then a decision of feature selection is made. This approach of feature selection, results in selection of feature details, at lower frequency resolutions also, which were discarded in the conventional CSS approach. To derive the spectral density of these obtained Db, power spectral densities (PSD) to the obtained Db are computed. PSD is defined as a density operator which defines the variation of power over different content frequencies, in a given signal \( x(t) \).
An example for the obtained Db for the linearized signal of figure 7 is shown in figure 8.

The Power spectral density (PSD) for a given signal \( x(t) \) is defined as,

\[
PSD, P = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2 \, dt
\]

Taking each BAND ‘\( I_i \)’ as reference, a PSD for each BAND, ‘\( PI_i \)’ is computed. The PSD features for the 4 obtained Db are then defined by,

\[
PI_i = PSD (I_i), \text{ for } i = 1 \text{ to } 4
\]

The BAND PSD’s are derived as,

\[
PB_i = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} B_{hi}(t)^2 \, dt
\]

From these obtained energy values, Db are selected based on a defined selection criterion, as outlined,

For obtained \( PI_i \), maximum \( PI \) is computed, defined by,

\[
MPI_i = \max(PI_i)
\]

For \( i = 1 \) to 4

if \( (PI_i \geq (MPI_i / 2)) \)

\( \text{sel}_{I_i} = I_i \)

end

Figure 7: Operational flow chart for Proposed LCEC approach
For these selected Db, ‘Sel_I,’ features are then computed by the approach of peak picking, as carried out in CSS approach. For each select BAND a maximum value is computed and all the coordinates above 60% of the pick value are taken as shape features ‘sf’. With this approach the finer frequency contents which were discarded in the CSS approach, were also given consideration for feature extraction. These approaches hence derive more informative feature information than CSS.

**Classification and Retrieval**

Training and testing are two operation stages used in this approach. Wherein, training process set of recorded images are processed in a sequence to extract the features. For every training image, the obtained features are buffered into an array termed as knowledge data base. During the process of testing the same operations are repeated over the test sample. The obtained query features are passed to a classifier to retrieve information’s from the knowledge data base. For the process of classification, a k-Nearest Neighbors (K-NN) classifier is used. The classifier is designed with a Euclidian distance based approach to obtain the best set of matches from the knowledge data base. The decision ‘D’ for the retrieval is derived as the minimum value of the Euclidian distance defined as,

\[ D = \min(E_{di}) \]

Where,

Euclidian Distance, \( E_{di} = \sqrt{\sum_{i=1}^{N} Q - dbf_i} \)

Where,

Q is the query feature and,

dbf, is the features trained in the data base.

**Experimental Results**

The 6 Db and the residual obtained are shown in figure 9. It is observed that BAND 1 and BAND 3 exhibits higher coefficients variation than the other two bands, hence more curvature information is present in these two functions. To select the required Db for feature extraction, a spectral density using power spectral density is used. The energy density for each band is as shown in figure 10.

The spectral energy density for each BAND is computed using, a power spectral density approach. Each BAND coefficients are averaged by the squared summation of its coefficients and energy is computed. From the BAND energy obtained, it is observed that, BAND 1 and 3 has comparatively higher energy density than the other two Db. This is observed to be synch with the observations made from the Db obtained as seen in above figure. Based on the energy derived, two highest energy density Db are selected, which is 1 and 3 in this case.
Similarity Measures

Retrieval result is not a single image but a list of images ranked by their similarities with the query image since CBIR is not based on exact matching. For a model shape indexed by FD feature \( f_m = [f_{m1}, f_{m2}, ..., f_{mN}] \) and a database indexed by feature \( f_d = [f_{d1}, f_{d2}, ..., f_{dN}] \) the Euclidean distance between two feature vectors can then be used for the similarity measurement,

\[
d = \sqrt{\sum_{i=0}^{N-1} |f_{mi} - f_{di}|^2}
\]

Where, \( N \) is the total number of sampled points on the shape contour.

Using the Fourier transformation of the feature vector the property of invariance is achieved. To perform the retrieval operation over the suggested approach a feature vector of query image is extracted and this feature vector is compared with each image feature vectors which were stored in the database in training phase. The similar images by measuring the similarity index between the query image and database images are then retrieved. To perform a shape depth analysis of the image retrieval system, shape depth feature extraction and processing model is developed. The retrieval system observations are presented in figure 14-17. The original test sample is shown in figure 13.. For the retrieval operation for a edge based coding is presented in figure 14(a), (b). A canny edge operator is used to derive the edge informations [50], and features are derived based on the obtained edge region to retrive informations. The top three classified observation and the best match retrieval is shown in figure 14(a) and (b) respectively. Figure 15(a) shows the the top retrieval results obtained for Contour based [1, 2] approach, and the top retrieval is shown in figure 15(b). For the CSS [3] based approach, the observations are shown in figure 16 (a) and (b) respectively. In figure 17, the retrieval observations based on the proposed LCEC approach is observed. From the obtained observations for the developed methods, it is observed that the proposed LCEC based approach retrieval shows better retrieval performance than the conventional approaches. This is obtained due to an inclusion of finer variation details in LCEC. Due to two variations selection process, the curvature of higher density are recorded as in CSS, however in the 2nd BAND selection, the second level curvature coefficients were also selected for feature description, which are totally discarded in all previous methods. This 2 level curvature selection results in higher retrieval accuracy.

![Figure 12: Extraction of Features from selected BAND-3](image)

![Figure 13: Test Sample](image)

![Figure 14: (a) Top 3-classification for Edge Based [3] coding (b) Top retrieved sample](image)

![Figure 15: (a) Top 3-classification for MSCP Based [13] coding (b) Top retrieved sample](image)

![Figure 16: (a) Top 3-classification for CSSI Based [14] coding (b) Top retrieved sample](image)
To evaluate the retrieval efficiency of the developed approach, the performance measures of recall and precision is made. The recall and the precision factor are derived from [7, 8], where the recall is defined as a ratio of number of relevant image retrieved over, total number of relevant image present. The Precision is derived as a ratio of number of relevant images retrieved to the total number of images retrieved. The recall and the precision factor is defined as:

\[
\text{Precision} = \frac{\text{No. of relevant images retrieved}}{\text{No. of images retrieved}}
\]

\[
\text{Recall} = \frac{\text{No. of relevant images retrieved}}{\text{No. of relevant images present}}
\]

The obtained recall-precision curve for the proposed system is outlined in figure 18. The observed precision for the proposed LCEC approach is observed to be higher than the conventional edge, contour and CSS based approaches. As the spectral information’s are more accurately represented with lower variations component as well. The descriptive features are observed to be more accurate in processing as in compared to conventional system.

The original sample of a uniform dimension of 256 x 256 is taken. The test sample is made to a uniform dimension to provide a generality in the proposed coding. A test sample taken for evaluation is shown in figure 19.

For the evaluation of the developed approaches over different noise variance the test sample is processed over salt and pepper noise with different value of noise variance. The noised effected samples passed for processing at different noise variance is shown in figure 20.

Figure 18: Recall-Precision curve for developed system

Figure 20: Noised sample at, (a) \(\sigma=0\), (b) \(\sigma=0.01\), (c) \(\sigma=0.02\), (d) \(\sigma=0.03\), (e) \(\sigma=0.04\), (f) \(\sigma=0.05\)
The process of DWT based band decomposition for multispectral coding is shown in figure 22. The original test sample is passed via hierarchical filter bank units to extract the high and low band resolution spectrums in multiple scale levels.

The obtained image samples after the DWT based coding is presented in figure 23. The obtained results at different noise variances are shown in figure 23 (a)-(e).

The decomposed bands of multi wavelet bands is shown in figure 24. The decomposition of multiple band per resolution could be clearly observed, each resolution band is further decomposed into 4 sub bands.
Figure 25: Recovered samples for SYM at, (a) $\sigma=0$, (b) $\sigma=0.01$, (c) $\sigma=0.02$, (d) $\sigma=0.03$, (e) $\sigma=0.04$, (f) $\sigma=0.05$

The obtained image samples based on the coding of multiwavelet decomposition is illustrated in figure 25 (a) – (e) under a noise variance of 0 to 0.05 respectively.

In the process of selective Hybrid coding the process of LMSE computation and estimation is carried out among each inter bands in a resolution band and a band selection process is executed to achieve the band selection process in multi wavelet bands. The selective band for the multi wavelet band shown in figure 24 is illustrated in figure 26. The process of encoding is carries over these selected bands, which reduces the overhead and as well provide higher PSNR due to the selection approach.

Figure 26: Selected Bands using S-SYM

Figure 27: Regenerated bands for SYM-wavelet coding

The processed bands are regenerated at the decoder side by the repetition of the decoded selective bands. A regenerated multi wavelet band for the given query sample is shown in figure 27.

Figure 28: Recovered samples for SYM at, (a) $\sigma=0$, (b) $\sigma=0.01$, (c) $\sigma=0.02$, (d) $\sigma=0.03$, (e) $\sigma=0.04$, (f) $\sigma=0.05$

As outlined in earlier sections, LCEC coding is improved over Curvature scale space coding. In the approach of contour coding, it is observed that large feature counts are obtained as the whole contour region is considered. However, a domain contour curvatures are the required shape regions for a given test image. The process of dominant curvature region detection is more effectively been illustrated in CSS [6] approach. Hence, taking the base of CSS coding, feature selection process is developed. LCEC is developed with the consideration of effective feature selection from all regions for CSS curve which were discarded in the conventional CSS based feature extraction approach.
In the process of CSS, the marked coefficient which lies at the higher regions is only selected. Wherein if observed it could be seen that only the dominant curvature peaks were taken under consideration. These peaks could be observed in figure 29. However, the curvature parts of the edge regions, which exist for a lower time period is eliminated. The low varying curvatures at the edge region is illustrated in figure 30, and its corresponding CSS representation is illustrated in figure 31.

They are observed to be diminished after a short interval and are not taken under consideration. However, the rough curvature of the test image contributes in its representation; hence they should also be considered. To achieve this, a 1-D linear interpretation of this obtained CSS is made. The average summation of each zero cross band derives the 1-D linear signal representation of the CSS curve. It could be seen that the Integrity of the dominant peaks are retained, and low – period curvatures are as well concentrated.

As the variational elements could be more dominantly been observed in BAND1 and BAND2, the spectral density is observed large in these signals. Considering, these 2 dominant bands features are then extracted. As these 2 bands concentrate most variation, the features when extracted will take both low and high varying elements under consideration. A comparative feature count table for the developed approach is as presented in table 1.

<table>
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<tr>
<th>Test sample</th>
<th>Feature Counts</th>
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<tr>
<td>S1</td>
<td>85 90 92 97</td>
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<tr>
<td>S3</td>
<td>89 94 96 100</td>
</tr>
<tr>
<td>S4</td>
<td>81 86 89 93</td>
</tr>
<tr>
<td>S5</td>
<td>86 90 93 96</td>
</tr>
<tr>
<td>S6</td>
<td>90 95 97 102</td>
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<td>S7</td>
<td>87 92 94 98</td>
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<td>S8</td>
<td>84 89 91 95</td>
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<tr>
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<td>88 93 95 99</td>
</tr>
<tr>
<td>S11</td>
<td>82 86 90 95</td>
</tr>
</tbody>
</table>

Feature counts of averagely 2000 values are minimized by the approach of CSS based approach. However the LCEC feature a count of 5 features is added up as low-duration feature inclusion. Though about 5 features is added to the CSS
feature, the efficiency of the system is observed to be improved. A classification is then performed on these extracted features and the obtained results are evaluated for system precision, classification ratio and computation time for the proposed system over the conventional benchmark systems.

**Figure 34:** True classifications for the developed LCEC Approach over conventional shape based classification system

**Table 2:** Observed Classification for different test samples

<table>
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<th>Test sample</th>
<th>True classification (%)</th>
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<td>S8</td>
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</tr>
<tr>
<td>S9</td>
<td>70</td>
</tr>
<tr>
<td>S10</td>
<td>76</td>
</tr>
</tbody>
</table>

The true classification for the developed approaches is evaluated on different test samples and classification ratio for the top 10 retrieved sample is computed. The LCEC approach results in better classification for a given test sample as in comparison to the conventional approach of edge, contour, and curvature scale space coding. An improvement of 8% is observed for the LCEC approach, in comparison to the CSS based coding approach.

The computation time is observed to be minimized by 0.8 sec in the LCEC approach, although features are increased, the search time is reduced, as the more effective features results in faster matching performance, which terminates the searching process more earlier than other methods. The obtained recall over precision observation for different test observations is presented in table 4.

**Figure 35:** Computation time plot for the developed LCEC over other shape based classifier

The observed precision for the developed approach is observed to be 97% for a recall rate of 10, wherein the conventional CSS based approach results to 94% for the same. In the case of recall rate set to 80, the improvement is observed to be 4% higher than the CSS method.
The limitations of edge descriptor and CSS representation of curvature scale space coding, wherein each variational component is derived using DWT coding. A lower dimension feature representation using scale space modeling is presented. The proposed approach of depth feature and LCEC approach, results in a robust retrieval technique which is invariant in representation, noise free in coding, and faster in processing. These properties of the proposed approach give the developed system a more effective application under resource constraint environment.

The next chapter presents the summary and conclusion remarks. A lower dimension feature representation using scale space modeling is presented. To optimize the feature selection process in this work, a new spectral based feature representation and selection process is presented. The approach of LCEC coding, is developed using a 1D linear representation of curvature scale space coding, wherein each variational component is derived using DWT coding. The spectral domain based coding results in proper band

### Table 3

<table>
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<tr>
<th>Feature Selection Method</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Recall</th>
<th>Precision</th>
<th>F-Measure</th>
<th>Time</th>
<th>Overhead</th>
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### Table 4: Observation of recall v/s precision for the developed system

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<thead>
<tr>
<th>Precision (%)</th>
<th>Recall Rate (%)</th>
<th>Edge Based Methods</th>
<th>Contour Based Methods</th>
<th>CSS Based Methods</th>
<th>Proposed Method</th>
<th>Using LCEC</th>
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selection resulting in accurate and lower feature coefficient selection. Due to consideration of lower band coefficients, lower curvature information's are also considered, which are discarded in CSS coding. This consideration leads to higher retrieval accuracy in spatial similar images. The contour coding for 3D samples is also developed based on a 3D-CSS feature representation. Wherein, the depth parameter is considered with the shape feature for image retrieval.

References


