Active Salient Component Classifier System on Local Features for Image Retrieval

S. Janarthanam¹*, S. Sukumaran² and M. Shanthakumar³

¹Department of Computer Science, Gobi Arts and Science College, Erode – 638452, Tamil Nadu, India; profsjana@gmail.com
²Department of Computer Science, Erode Arts and Science College, Erode – 638112, Tamil Nadu, India; prof_sukumar@yahoo.co.in
³Department of Computer Science, Kamban College of Arts and Science, Coimbatore, India; professorshanth@gmail.com

Abstract

Objectives: The objective of the examined active salient component classifier is to extract the image features from the visual substance through a novel non-parametric example based positioning methodology to utilizing comparability and learning strategies. Methods/Statistical Analysis: To establish the authenticity to avoid improper retrieval on online based image classification system called, lite Dynamic Pattern Extraction Algorithm (DPEA) for Image Classification and salient image extraction algorithm is designed. DPEA Algorithm on each benchmark dataset works on user query basis and reducing the overhead incurred during user query processing by applying labeling process. Next, by retrieving salient features on images with zero mean for each client query and each image retrieval reduces the execution time and complexity as the database does not maintain the related features. Finally, the Potential image Classification and retrieval prevents the unauthorized user modification on image data, therefore improving the reality. Here a Web Image Dataset (NUS-WIDE) created by lab of media search in National University of Singapore. The computer vision CIFAR-10 dataset, Modified National Institute of Standards and Technology database of USA (MNIST) dataset is used for experiment. A series of simulation results are performed to test the image retrieval efficiency, execution time, performance fitness for obtaining efficiency of image data handling and measure the effectiveness of DPEA Algorithm. Findings: The tests were directed on the dataset for image classification and retrieval on each region of the images. The Proposed DPEA offers better performance with an improvement of the data confidentiality by 18.72%, reduces execution complexity by 7.98%, reduces average retrieval overhead by 6.65% and also minimize retrieval complexity by 15.57% compared to existing algorithms of LFDA, PCA and PCCA respectively. Application/Improvements: It can be further extended with implementation of new retrieval techniques with different parameters which improves more retrieval efficiency and performance integrity.

Keywords: Bit Streams, Component Analysis, Dynamic Patterns, Feature Extraction, Image Retrieval, Salient Features

1. Introduction

In computer vision and multimedia system a variety of effective classifier systems are associated with Content-Based Image Retrieval (CBIR) to retrieve images from large image database based on features. In unrestrained world of multimedia applications, image similarity identification is a fundamental research task in several communities. The challenge of the research is to design effective feature representation and to study the distance

*Author for correspondence
similarity functions over the feature space. In online image search and retrieval most of the images are usually not annotated with proper tags, and many of them are completely unlabeled. In ancillary, many of the associated tags are usually noisy, irrelevant, and typically incomplete for describing the semantic contents of the images. Refinement of image viewpoints is a challenge for image search approaches used to apply the regular indexing and retrieval techniques to the web image search task.

CBIR systems can recover pictures in light of low-level substance are extremely basic to get the successful resultant pictures however lies in the trouble of giving and recognizing a proper question to depict the client's pursuit aim. The picture inquiry by client system on worldview increment underlay and appropriation of sight substance viably retrieving comparable sample images in online has turned into a clear and troublesome issue. So the mixed media content examination turns out to be perceived for answers for an inexorably dynamic range for innovative work. Whatever remains of the paper is composed as takes after segment 2 introduces the exploration approach and points of interest diverse sorts of learning. Area 3 points of interest the proposed technique outline with example extraction system and the calculation. Area 4 demonstrates the outcomes and they got by trial tests and contrasting and different systems. At last the conclusion is exhibited in Section 5.

2. Research Methodology

The objective of this examination procedure is to enhance the execution of picture retrieval and recovery by mining rich tag and visual substance through a novel non-parametric example based positioning methodology as opposed to utilizing comparability and learning strategies.

2.1 Kernel Based Learning

The kernel based learning approaches to gain information consequently from picture databases and starting reviews have endeavored to take in bit capacities or networks from marked and unlabeled information as minimized pieces idealized bit learning, diagram based unealthy portion learning, and non-parametric bit learning. These techniques regularly take after a transitive setting and furthermore hard to be connected in an internet learning situation. The bit grids catch the rendering measure from

\[ k(x_i, x_j) = e^{-\frac{d(x_i, x_j)^2}{2\sigma^2}} \]  

(1)

The distance value \(d(x_i, x_j)\) permits to pick the histogram prompts high computational handling of large databases. The bit based learning is a two-arrange technique that procedures learning and similitude capacities for preparing the classifier are isolated. The objective of the proposed task is to take in the portion for measuring representation between the pictures and queue the semantics by investigating both printed and visual substance. The bit learning undertaking is to viably investigate the literary substance of social pictures are to upgrade the learning value \(k\) by amplifying the dependence amongst \(x\) and \(\sigma\). The set is a liable to change if the labelled or unlabelled pictures must be recomputed. The portion values must be performed with multilaceted nature \(O(m \times n)\), with m number of marked pictures with in n number of pictures in the database. The primary downside of the technique is the sudden mark can prompt no change. Consider the label as positive then the grouping is highly enhanced but generally no change on the distance value. Since the productivity of the techniques depend upon all labels as often as possible but not identical. The distance metric learning to upgrade the Mahalanobis distance and bilinear likeness work between the information delineations are scientifically communicated in condition (2) and (3) as,

\[ D_M(x_i, x_j) = \sqrt{(x_i - x_j) \times M(x_i - x_j)} \]  

(2)

\[ S_M(x_i, x_j) = x_i^T M x_j \]  

(3)

The approach is basically to gauge the closeness separate formation in view of visual substance both neighborhood and worldwide visual elements extricated from each pictures. To address the confinement of the general Visual Rank approach, display a novel non-parametric portion positioning way to deal with take in a successful visual extent \(k\) protects the semantics by misusing both visual and printed substance of social pictures. To locate an ideal Mahalanobis distance \(M\) from the training information the current intentions are intended to remove measurements on low-dimensional elements are computationally wasteful and non-adaptable for high
2.2 Iterative Discriminant Learning

The disadvantages of kernel based learning approach taking in the Iterative Discriminant Learning (IDL) ready to fabricate the most regenerative classes for the client to recover the most feasible classes. Likewise concentrating on nonlinear iterative clump approaches, the computational speed contrasted with first request inclination drop strategies, the preparation set is required to limit the exact hazard. In discriminative methodologies the regulated adapting adequately abuses the relating scanty flag deterioration in picture characterization assignments, and proposes a powerful technique for taking in a common lexicon approach.

The key thought is to learn at the same time a solitary shared word reference and the models for a blended generative and discriminative detailing. Not quite the same as pair wise and generative strategies, the discriminative techniques effortlessly embed different qualities of groupings and take in the data from both positive and negative examples in given benchmark dataset. A key element of discriminative information requires settled length highlight vectors. In light of succession data properties or optional structure data, for example, SVM-DRI5 strategies depend on part, for example, SVM-Pairwise16,17, SVM-LA, theme bit, jumble18, SW-PSSM, profile piece10,19. The cutting edge execution on the benchmark datasets was accomplished by utilizing a Local Fisher Discriminant Classifier (LFDA)19. While a shut shape answer for the Mahalanobis network requires an Eigen examination of a d×d disperse basis. For substantial d, the dimensionality of the information lessened utilizing vital segment investigation (PCA). The PCA can annihilate discriminant highlights vanquishing the paybacks as opposed to utilizing the segment way to deal with protect discriminant highlights for decreasing the measurement of the issue to N×N eigen deterioration, where N << d is the quantity of pictures. The better execution on the dataset20 accomplished utilizing a versatile limit approach. Mutually taking in the separation metric and a versatile thresholding guideline scales ineffectively with computational many-sided quality O(d2), d is the measurement of the elements vector xij. For other option to utilize a strategic capacity for inexact the loss of worldwide ideal capacity accomplished by iterative slope seek along p as in Pair wise Constrained Component Analysis (PCCA)21 and furthermore in Probabilistic Relative Distance Comparison.

The IDL needs to address the issue utilizing the extra degrees of flexibility accessible to amplify the between class threshold22. The circulation p, the desire administrator is approximated by a specimen normal S. Practically speaking each measurement has two subsets contains the marks xi with the end goal that hk(xi)=0 and has marks xi fulfills hk(xi)=1. For online the inquiry x has pre-registered and hidden away the look-into tables by the accompanying question subordinate qualities are appeared in condition (4),(5) and (6),

$$\beta_k^0 = d(g_k(x), \alpha_k^0) = (g_k(x) - \alpha_k^0)^2$$

$$\beta_k^1 = d(g_k(x), \alpha_k^1) = (g_k(x) - \alpha_k^1)^2$$

$$d_E(x, y) = \sum_k b_k^h(y)$$

The separations for each measurement as made-up effectively by gathering the measurements of a comparative approach connected to a more extensive scope of parallel inserting systems with the assistance of meager grid. For huge databases the processed qualities are immaterial with the subdivide the vector space into k measurements, the double sub-vectors fits 1 byte, the pre-gathered and diminished qualities put away in the query table. The distinctions of various component portrayals of each example in the educated separation measurements are limited and have the same semantic disturbance.

3. Proposed Method

The key segment for extricating patterns is utilized to separate the applicable examples from the extraction errand. Extraction of valuable examples is troublesome, tedious assignment, the examination endeavors concentrated on taking in the extraction rules from preparing illustrations gave by the client. In this paper portray a calculation for strong extraction of bits piece and blending a Gaussian pseudo-irregular grouping of bits. The bits are extricated by thresholding projections onto irregular smooth examples created by a client determined key qualities. To make the methodology, to supplant modes with low-recurrence without dc (i.e., having zero mean) arbitrary level patterns created a mystery key with coefficients proportional to projections onto the patterns. For
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3.1 Designing Requirements

The outline necessities are utilized as a part of two terms comparable and unique. Consider the region square B1 is like B2 if B2 can be acquired from B1 by applying some basic picture operation, for example, differentiation and shine change, gamma amendment, histogram evening out and extending, obscuring, honing, edge upgrade, non-direct separating, diminishing the shading profundity, printing and ensuing filtering, or watermarking. Given picture I isolate into squares of 64×64 pixels for substantial pictures, bigger piece sizes could be utilized. Utilizing a mystery key K, numbers particularly connected with created N arbitrary grids with sections consistently appropriated interim [0, 1]. The extraction depends on threshold projections onto N key-wards on irregular smooth examples.

3.2 Threshold Extraction Vector

Low-pass channel is over and over connected to every arbitrary lattice to get N irregular smooth patterns. All patterns are subtracting the mean from each considering the square and the example as vectors, the picture piece B is anticipated on each example Pi, 1 ≤ i ≤ N and the outright esteem is contrasted with an Th and get N bits bi

\[ b_i = \begin{cases} 0 & \text{in the event that } |B\times P_i| < Th \\ 1 & \text{in the event that } |B\times P_i| \geq Th \end{cases} \]

Since the examples Pi have zero mean, the projections don’t rely on upon the mean unclear estimation of the piece and just rely on the varieties in the square itself. The disseminated projections are reliant and balanced by inexact portion of the bits bi are zeros and half are ones will ensure the most astounding data substance of the separated N-tuple. The versatile edge for the image operations altogether changes the conveyance of projections as complexity conformity. An extraction of example matches segments, and tests arrangement of syntactic connections between the parts are shows an occasion. Different parts are incorporated into the example just expected to make connections between the part filling components. Learning Information Extraction Policies (LIEP) makes potential examples from an occasion via seeking the arrangement of connections relate every one of the occasions. Picture preparing strategies give a compelling example acknowledgment handling. To conquer the issues of the layout coordinating operations are performed on two dimensional pictures also as in one dimensional. The one dimensional conditions are utilized to figure estimations for contribution to the example acknowledgment calculation decides trouble areas.

3.3 Pattern Classification

The pattern acknowledgment system arranges information in light of factual dispersion and the estimation of information. In a perfect world, the method is utilized on estimation information is regularly conveyed the base blunder rate classifier approximates an ordinary appropriation. The adequacy of the technique relies on upon the dispersion of the information in respect to the ordinary model and the separations between the mean of class estimations. The area of crossing points characterized utilizing the condition (7),

\[ g(x) = -\frac{1}{2} \left( x - \mu \right)^T \Sigma^{-1} \left( x - \mu \right) - \frac{1}{2} \log |\Sigma| + \log P(\omega) \tag{7} \]

the variable x is the vector of estimation qualities, µ is the mean estimation of the ith estimation class, P(ωi) is the from the earlier likelihood of that nature in the state ωi and σ is characterized as the lattice of standard deviations with components characterized by the normal estimation of the class estimation values and class implies as appeared in the Condition (8),

\[ \sigma^2 = E \left[ (x_i - \mu_i)(x_j - \mu_j) \right] \tag{8} \]

For pattern acknowledgment characterization issues, quadratic discriminant examination parameterizes choice limits. The coordinating affectability stayed away from shaping layouts of items and connecting with parallel limit pictures. Despite the fact that the classifier exchanges the lighting variety issue to the thresholding phase of the proposed algorithm.
3.4 Lite Dynamic Pattern Extraction Algorithm

Algorithm

Start
Instate n, c₁, μ₁, μ₂, μ₃, ……, μ (selected arbitrarily)
Do characterize n tests as indicated by closest μᵢ
Recompute μᵢ
Until no change μᵢ
Return μ₁, μ₂, μ₃, …… μₖ

Discover (cᵢ, cᵢ₊₁) {
If (cᵢ, cᵢ₊₁) connected then
on the off chance that immediate connections (cᵢ, cᵢ₊₁, R)
at that point return R
else
While (pick next_pattern) {
rels1:=find_connections (cᵢ, moderate)
rels2:=find_connections (cᵢ₊₁, moderate)
rels :=( rels1+rels2)
else
Disappointment
}
Assemble new example {B.Pᵢ} {
Most elevated Accuracy: =0; Result: =failure
Do n times {
rels:=find_relationships_roll_fillers (pi)
In the event that (rels! =failure)
Point gets next examples (rels) / Conforming RF
Acc: =Compute_f_score_ (designs)
In the event that (Acc > Highest precision) then {
Most elevated precision: =Acc Result: =Pattern
}
Return (result)
}

End.

For the significance between the picture highlights in the database or an inquiry picture is considered as the fundamental favorable position of the procedure. Likewise to test a subpart of the picture and the dataset has a place with the elements of the picture in the database given by condition (9)

\[ C(P, K) = \frac{\sum_{j=1}^{a} \sigma_j \times K}{\sqrt{\sum_{j=1}^{a} d_j \times \sum_{j=1}^{a} k_j k_{j+1}}} \]  

(9)

The P is the picture pattern scheme from the database and K is the inquiry picture, K and P ought to be in same measurement also, the query image K is the piece of the picture strategy P, if the edge approaches close to 1 utilizing the relationship esteem, most important pictures can extricate.

4. Experimental Result

The proposed design performed on the picture database and sub-pictures. By the way the power and effectiveness are expanded and furthermore lessens the inquiry space, the quantity of relics and distortors exhibit in the entire image. The tests were directed on the dataset of picture recovery including NUS-WIDE, CIFAR-10 and MINST. For each dataset, the pictures are part into a preparation set and a testing set. The preparation set to take in the parameters and utilize the question set to contrast the contending strategies and calculations with break down the proficiency of various segments to assess the impact to the last outcomes.

In the proposed set of rules, the pictures sized to 64×64 for the NUS-wide dataset, CIFAR10 and MNIST, to 32×32 and 24×24 respectively. The Parameter inside the equation (4) and (5) is ready as 0.001 in all of the experiments. Every iteration pix are selected according to class labels like 10, 20 snap shots selected. As a way to accelerate the schooling method, we randomly pick 200 photographs to calculate the gradient. Observe that the similarity matrix S in Equation (2) is also constructed according to the selected pictures in every new release, and avoids constructing the overall similarity matrix additionally scalable to large scale dataset. The overall performance of the proposed set of rules is compared with all other baseline techniques and computes the measures for each benchmark datasets. For each of the schooling or take a look at images the global measures, the mean of the measures are obtained.

\[ \text{Precision} = \left( \frac{A}{A + C} \right) \times 100 \]  

(10)

right here A be quantity of relevant instant images retrieved, C variety of inappropriate images retrieved and A + C, overall quantity of irrelevant + relevant pictures retrieved from equation (10) the derived function averages are shown within the Equation (11) as follows

\[ \text{Average precision(AP)} = \frac{1}{k} \sum_{i=1}^{k} C \frac{C}{P(\omega_i)} \]  

(11)

where ‘C’ is the range of floor reality functions of the image, P(ω) is the rank position of the Cᵗʰ ranked ground
reality capabilities, and ‘precision’ and ‘review’ are respectively the precision and don’t forget for the annotation decisions and $S_y$ be the similarity matrix fee related to the ranking role.

$$\text{Interpolated Average precision}(\text{IAP}) = \frac{1}{k} \sum_{j=1}^{N} \frac{C_j}{S_y}$$  \hspace{1cm} (12)

In which $j = 1, 2, \ldots, N$. observe that AP and IAP depend handiest on the self-belief scores, at the same time as the F measure handiest depends on the annotation choices. Since the range of ideas per photograph is small and variable, the AP and IAP can be computed the usage of the rank positions the use of every possible price of recall, in preference to the use of fixed values of recall.

$$\text{Recall} = \left( \frac{A}{A+B} \right) \times 100$$  \hspace{1cm} (13)

Wherein A be the range of applicable photos retrieved and B denotes the range of applicable photographs now not retrieved also $A+B$ is the entire number of applicable images. The usage of the Equations (12) and (13) the fit degree of the algorithms is calculated by using the Equation (14).

$$\text{F Measure} = \frac{2 \times \text{(precision \times recall)}}{\text{(precision + recall)}}$$  \hspace{1cm} (14)

After obtaining the approach, the measures may be called MAP (Mean Average Precision), MIAP (Mean Interpolated Average Precision) and MF (Imply F-Measure), respectively. For the IAP the geometric suggest is also used for the upgrades on hard ideas.

### 4.1 Retrieval Efficiency on NUS-WIDE Dataset

The NUS-WIDE is a web photograph dataset created for Media seek in countrywide university of Singapore. The dataset includes low-degree functions extracted pix along with sixty four-D color histogram, a hundred and forty four-D shade correlogram, 73-D aspect path histogram, 128-D wavelet texture, 225-D block-sensible coloration moments and 500-D bag of phrases based totally on SIFT descriptions; and floor-truth for eighty one ideas that can be used for evaluation. It’s miles apparent to acquire very competitive results with its constant-length variations. In evaluation, while function extraction is taking into account, performance could be a awesome benefit of our stop-to-quit framework.

In Figure 1 the binary code period is illustrated on NUS-WIDE Dataset. The MAP results with exceptional bit period and the retrieval performance of the present and proposed techniques. The proposed approach outperforms comparatively with the existing techniques.

![Figure 1. The retrieval efficiency on NUS-WIDE Dataset.](image)

### 4.2 Retrieval Efficiency on CIFAR-10 Dataset

CIFAR-10 is a longtime computer-imaginative and prescient dataset used for object recognition, Subset of the 80 million tiny pictures dataset and includes 32 x 32 coloration photos contained in item lessons, with 6000 photos consistent with magnificence. It was accumulated via Alex Krizhevsky, Vinod Nair and Geoffrey Hinton. Random sample of 10K query pictures 1K pictures per item magnificence for take a look at set and use the rest as the education set.

The MAP effects with exclusive bits length shown in Figure 2. The proposed algorithm achieves almost 15.44% efficiency charge increased than the nearby Fisher Discriminant Classifier (LFDA) method and shows the comparative retrieval efficiency of the proposed DPEA increases the 10.12% retrieval charge than the Pair wise restricted issue evaluation.

![Figure 2. The retrieval efficiency on CIFAR-10 Dataset.](image)
4.3 Retrieval Efficiency on MNIST Dataset
The MNIST database of handwritten digits has a schooling set of 60,000 examples and a check set of 10,000 examples. The subset of a bigger set available from NIST, the digits had been length-normalized and focused in a hard and fast-length photo all of the experiments are performed for evaluating the overall performance of the proposed system on every dataset primarily based on the bit duration q and the chosen k bits with the largest weights to calculate the similarity according to condition. The retrieval performance related to numerous lengths is proven.

In Figure 3 the code length and MAP results with completely different bit length and the retrieval potency of the present and projected strategies are presented. The projected algorithms beat out relatively with the present information strategies facts the proposed DPEA method has the higher retrieval efficiency relatively with the alternative present strategies on MNIST data set.

![Figure 3. The retrieval efficiency on MNIST Dataset.](image)

4.4 Performance Analysis on Bench Mark Dataset
The performances of the proposed algorithm for exceptional datasets also are pronounced in addition evaluation. If variety of bits is greater than the overall performance might be insignificant. By diminishing the limit linkage methodology, the quantities of little size bunches are extricated in a various leveled way, empowering a more nitty gritty investigation of the informational index.

For this examination, the essential properties of the each datasets be looked at Table 1, for print thickness, highlight shading, reflectance and surface, of which just the two last may have relations with the quantitative components utilized here to portray the surfaces. The execution estimations in view of web, arbitrary and co-event benchmark information are prepared and tried for the condition of craftsmanship execution under normal bits block.

Contrasting with every fundamental strategy the proposed method by the algorithm is greatly improved to recover the examples on both on the web and disconnected techniques Re-distinguishing proof of separation crosswise over disjoint perspectives is a critical issue in insightful reconnaissance, especially to restrict the utilization of taken datasets acknowledgment are categorised and mentioned in Table 1.

![Table 1. Complete class dispersal depiction on benchmark datasets](image)

| Algorithmic Procedure | Co-event Execution Rate | Precision Rate | Recall Rate |
|-----------------------|-------------------------|----------------|-------------|
| LFDA                  | 55.20                   | 51.72          | 49.70       |
| PCA                   | 50.64                   | 54.64          | 53.17       |
| PPCA                  | 53.90                   | 59.67          | 62.09       |
| DPEA                  | 71.50                   | 70.95          | 75.89       |

It is additionally an establishment of danger recognition, occasion understanding and numerous other reconnaissance applications over the specified restrictions of datasets under normal data shown and tabulated in Table 2. Regardless of impressive endeavors made because of the sensational varieties created by the diverse perspectives and changes with random and co-occurrence base line data are trained and tested for the state of art performance.

![Table 2. Performance fitness Comparison of the recommended proposal](image)

| Algorithmic Procedure | MAP   | MIAP  | MF   |
|-----------------------|-------|-------|------|
| LFDA                  | 0.115 | 0.096 | 0.054|
| PCA                   | 0.719 | 0.689 | 0.553|
| PPCA                  | 0.589 | 0.541 | 0.454|
| DPEA                  | 0.707 | 0.727 | 0.767|

5. Conclusion
This paper provided a notable lite dynamic pattern extraction algorithmic method by integrating characteristic getting to know and hash feature studying into a joint optimization framework via deep convolutional...
neural networks. The similarity evaluation components delivered within the deep hashing learning systems are to make sure photo adjacency and consistency. The proposed DPEA algorithm validated the results on popular image retrieval benchmark datasets, no longer simplest outperforming in terms of retrieval accuracy, however also significantly improving the flexibility of assorted duration hashing over the retrieval and classification methods.

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