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Research Article

Content Based Image Retrieval (Cbir) Using Hierarchical Nested Dynamic Clusters

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Abstract: In Content-Based Image Retrieval (Cbir) System, Query Results Of Images Are Searched And Sorted From The Image Database By Feature Similarities Based On The Given Query. Many Of The Image Retrieval Systems Extract Specific Features From A Query Image And Compare These Features With The Corresponding Pre-Computed Features Of All The Images In The Database. Still, Growing Size Of The Database Results In Long Search Which Delays That May Be Unacceptable In Many Practical Situations. Our Approach To Solving This Problem Is To Create Image Representation, An Image Indexing Scheme And By Grouping The Images Beforehand Based On The Content, So That At The Time Of The Query, Only The Relevant Set Of Clusters Need To Be Examined. The Clustering Must Be Performed In Such A Way That The Retrieval Accuracy Is Not Sacrificed In This Process

Keywords:Clustering, Query, Retrieval Models, Search Process.

1. Introduction

Content-Based Image Retrieval Has Become An Important Research Topic In Recent Years. Research Interest In This Fieldhas Escalated Because Of The Proliferation Of Image Data In Digital Form. The Growing Popularity Of The Internet, Theintroduction Of New Consumer Products For Digital Image, And The Emergence Of Digital Standards For Televisionbroadcasting Have Resulted In A Greater Demand For Efficient Storage And Retrieval Of Multimedia Data. Content-Based Retrieval Systems For Image Based On Various Image Features Have Been Presented.

Many Of The Image Retrieval Systemsextract Specific Features From A Query Image And Compare These Features With The Corresponding Pre-Computed Features Of Allthe Images In The Database. The Search Time, Therefore, Increases Linearly With The Size Of The Database. Efficient Feature Representationsand Similarity Measures Have Been Used To Speed-Up The Search Process.

Still, Growing Size Of The Database Resultsin Long Search Which Delays That May Be Unacceptable In Many Practical Situations. Even If The Time Required To Compare Two Imagesis Very Short, The Cumulative Time Needed To Compare The Query Image With All Database Images Is Rather Long And Is Probablylonger Than The Time An Average User Wants To Wait.To Achieve The Scalability Of Search To Large Databases, It Must Be Ensured That The Search Time Does Not Increase Linearly Withthe Database Size.

Our Approach To Solving This Problem Is To Create Image Representation, An Image Indexing Schemeand By Grouping The Images Beforehandbased On The Content, So That At The Time Of The Query, Only The Relevant Set Of Clusters Need To Be Examined. The Clustering Mustbe Performed In Such A Way That The Retrieval Accuracy Is Not Sacrificed In This Process. Retrieval Accuracy Here Is Measured Interms Of The Retrieval Obtained With Exhaustive Search.

A Technique Based On A Tree Structured Vector Quantizer And The Triangle Inequality For Fastsearch Has Been Presented In Hierarchical Cluster. Both These Techniques Require That The Similarity Measures Used To Compare Theimages Be A Metric, *I.E.*, The Similarity Measure Satisfies The Triangle Inequality. However, Many Useful Similarity Measures Donot Satisfy The Triangle Inequality Measure. Indexing Techniques Have Been Proposed For Fastrange Search. However The Large Dimensionality Of The Feature Vectors May Be A Problem For These

Indexing Techniques. Dimensionalityreduction Techniques Using Principal Component Analysis Or Orthogonal Transforms Can Be Used To Reduce The Featuredimension To A Manageable Number.

Performance Comparison Of Different Indexing Structures Has Been Presented In This Resear Study.The Technique Presented Here Does Not Explicitly Place Any Restriction On The Feature Dimension Nor Does It Use The Triangle Inequalityproperty.Here We Present A Technique For Image Retrieval Based On Hierarchical Structure From Large Databases.

The Goal Is To Group Similar Images Intoclusters And To Compute The Cluster Centers, So That During Retrieval, The Query Image Need Not Be Compared Exhaustively Withall The Images In The Database. To Retrieve Similar Images For A Given Query, The Query Image Is Initially Compared With All Thecluster Centers. Then A Subset Of Clusters That Have The Largest Similarity To The Query Image Is Chosen And All The Images In Theseclusters Are Indexed With The Query Image.

The Clustering Technique Is Not Directly Dependent On The Nature Of Similarity Measureused To Compare The Images, So This Technique Can Be Used For Any General Similarity Measure. The Experimental Evaluationshows That This Clustering Based Indexing Technique Offers An High Retrieval Accuracy With A Considerable Reduction In Thenumber Of Similarity Comparisons Required. Experimental Evaluation With Databases Of Different Sizes Shows The Scalability Ofthe Technique.

In This Research Study, Image Retrieval Are Performed In Three Ways,

- Hierarchical Clustering
- Hierarchical Nested Clustering
- Hierarchical Nested Dynamic Clustering

The Following Parameters Are Used To Evaluate The Performance Of The Above Algorithms

- Image Representation
- Image Indexing
- Image Retrieval
- Execution Time

2. Hierarchical Clustering

Hierarchical Clustering (Hc) Algorithms Organize Data Into A Hierarchical Structure According To The Proximity Matrix. The Results Of Hc Are Usually Depicted By A Binary Tree Or Dendrogram. Clustering Algorithms Partition Data Into A Certain Number Of Clusters (Groups, Subsets, Or Categories).The Idea Is Clusters Are Retrieve Image From Convolution Neural Image Sets During The Search Time.

Image Retrieval Using Hc Algorithm From The Image Collections Involved With The Following Steps.

- Image Representation Is Based On Convolutional Neural Network Image Set Such As Alexnet
- Apply Image Indexing Using Hierarchical Clusters.
- Image Retrieved Using Similarity Measure With Euclidian Distance
- Calculate The Execution Time Of Image Retrieve From Given Database.

2.1 Image Representation

In Hierarchical Clustering, Alexnet Which Employed For Image Representation, It Is An 8-Layer Convolutional Neural Network Was Used For Image Representation. This Network Proved In Alexnet’s First Layer, The Convolution Window Shape Is 11×1111×11. Since Most Images In Imagenet Are More Than Ten Times Higher And Wider Than The Mnist Images, Objects In Imagenet Data Tend To Occupy More Pixels. Consequently, A Larger Convolution Window Is Needed To Capture The Object. The Convolution Window Shape In The Second Layer Is Reduced To 5×55×5, Followed By 3×33×3. In Addition, After The First, Second, And Fifth Convolutional Layers, The Network Adds Maximum Pooling Layers With A Window Shape Of 3×33×3 And A Stride Of 2. Moreover, Alexnet Has Ten Times More Convolution Channels Than Other Convolutional Neural Network.

2.2 Image Indexing

Image Indexing Is A Technique Used To Index The Image Database In Hierarchical Clustering. To Form The Hierarchical Clustering, Calculate The Similarity Between All Images In A Database Is Precomputed.

After Clustering, An Appropriate Center Has To Be Obtained For Each Cluster. Since, Every Image Is Represented Ashistograms Corresponding To Thepartitions; It Is Apt To Use A Similar Representation For Cluster Centers. A Simple Representation Would Be The Average Of Histograms Of All The Images In The Cluster. Since The Number Of Images In Each Cluster Can Be Large, Averaging Over All The Images May Be Computationally Expensive.

One Solution Is To Find A Smaller Number Of Representative Images And Use The Averages Of Their Corresponding Histograms To Represent The Cluster Center. In The Following Discussion, The Maximum Number Of Representative Images For A Cluster Is Limited To Representative Image. These Representative Images Have To Be Chosen Carefully So That The Cluster Center Computed From Them Is Close To All The Images In The Cluster. The Tree Structure That Is Obtained As A By-Product Of The Clustering Algorithm Can Be Effectively Used To Select The Representative Set Of Images.In This Way The Images Are Indexed In Hierarchical Clustering.

2.3 Image Retrieval

Image Retrieval Are Performed By Using Similarity Measures Between The Clusters From Image Database, It Is Computed By Summing Up The Similarity Measures Of All Pairs Of Images In The Image Database, And Hence The Computation Grows As The Square Of Number Of Images Present In The Two Clusters.

$$S_{m,t} = \frac{P_{(N_l+N_k)}S_{l,k} + P_{(N_l+N_t)}S_{l,t} + P_{(N_k+N_t)}S_{k,t} - P_{N_l}S_{l,l} - P_{N_k}S_{k,k} - P_{N_t}S_{t,t}}{P_{(N_l+N_k+N_t)}}$$

2.4 Execution Time

The Execution Time Of The Hierarchical Clustering Approach Was Tested Onseveral Randomly Selected Queries And Compared With (I) No Clustering Or Hierarchical Structure And Direct Comparison Of The Query Image With Each Of 30,000 Images (Ii) Plain Clustering With No Hierarchical Nested Structure. The Comparison Starts At The Top Layer First And Continuous At The Lower Layers; However, Only With The Clusters Correspond With The Winner Cluster Determined At The Layer Above And The Estimated Execution Time Of Hierarchical Clustering Are 0.0017 Seconds

3. Hierarchical Nested Cluster

Hierarchically Nested Data Clusters Are Structured In Which Data Clusters At Higher Layers Represent One Or Multiple Clusters At A Lower Layer Based On Mean Values Of The Cluster Centers. The First Layer Clusters Are Generated Based On Feature Representations Derived From The Cnn Model. Data Clusters Are Formed By Grouping The Relevant Data Points Using A Partition-Based Clustering Approach Known As K-Means Clustering

3.1 Image Representation

Image Representation In Hierarchical Clustering Nested, The Visual Objects Or Scenes May Undergo Various Changes Or Transformations, And It Is Infeasible To Directly Compare Images At Pixel Level. Usually, Visual Features Are Extracted From Images And Subsequently Transformed Into A Fix-Sized Vector For Image Representation.

The Images Were Collected From The Web And Labeled By Human Labelers Using Amazon’s Mechanical Turk Crowd-Sourcing Tool. Starting In 2010, As Part Of The Pascal Visual Object Challenge, An Annual Competition Called The Imagenet Large-Scale Visual Recognition Challenge (Ilsvrc) Has Been Held. Ilsvrc Uses A Subset Of Imagenet With Roughly 1000 Images In Each Of 1000 Categories.

Alexnet Is The Name Of A Convolutional Neural Network Which Has Had A Large Impact On The Field Of Machine Learning, Specifically In The Application Of Deep Learning To Machine Vision. It Famously Won The 2012 Imagenet Lsvrc-2012 Competition By A Large Margin (15.3% Vs 26.2% (Second Place) Error Rates). It

Consisted Of 11×11, 5×5,3×3, Convolutions, Max Pooling, Dropout, Data Augmentation, Relu Activations, Sgd With Momentum. It Attached Relu Activations After Every Convolutional And Fully-Connected Layer.

3.2 Image Indexing

The Introduced Database Was Indexing Aims At Arranging And Structuring The Image Database Into A Simple Yet Effective Form Of Data Clusters And Hierarchies. Hierarchically Nested Data Clusters Are Structured In Which Data Clusters At Higher Layers Represent One Or Multiple Clusters At A Lower Layer Based On Mean Values Of The Cluster Centers. The First Layer Clusters Are Generated Based On Feature Presentations Derived From The Cnn Model. Data Clusters Are Formed By Grouping The Relevant Data Points Using A Cluster Centre Point.

Deep Learning Methodology Combined With Distance-Based Learning And Gaussian Kernel Features Can Be Seen As Recursive Supervised Algorithm To Create New Features, And Hence Used To Provide Optimal Feature Space For Any Classification Method.

The Final Step After Forming The Hierarchically Nested Data Clusters Is To Find The Cluster Which Contains The Most Similar Images To A Query Image. We Applied Recursive Similarity To Measure A Similarity Between The Query Image And All Images Inside Each Cluster Recursively. The Main Idea Of The Recursive Similarity Function Is To Estimate The Probability Function By A Cauchy Type Kernel And To Recursively Calculate It. The Method Is Also Applied For Novelty Detection In Real Time Data Streams And Video Analytics. The Recursive Calculation Allows Us To Discard Each Data Once It Has Been Processed And Only Store The Accumulated Information In Memory

3.3 Image Retrieval

To Begin A Search, The User Has An Example Image To Submit As A Query. The Cbir System Accesses The Images In The Database, Matches The Query Against The Information In The Database, And Scores The Images In Terms Of Similarity. The Matching Is Based On Chromatic And Texture Features With Equalweights. The Top *K*-Best Images Are Returned As Results. The Methods Are Called Winners To Take All.Self- Organizing Maps Are A Powerful Tool For Categorization And Classification That Involve Clustering Or Grouping Items Of A Similar Nature. Continuous-Valued Vectors That Represent Chromatic And Textural Features Are Presented Sequentially To The Map In Time Without Specifying The Desiredoutput.

The Images That Are Grouped Into The Category Are Presented In The Right Frame As Result. Since Similar Images Are Automatically Grouped Into The Clusters, Which Is Called Winners To All In The Node And Users May Proceed To The Nodes For Feature Images Observed Visual Similarity Of The Labeled Images On The Clusters.

3.4 Execution Time

The Execution Time Of The Hierarchy Of Nested Clusters Was Tested Onseveral Randomly Selected Queries. The Comparison Starts At The Top Layer First And Continuous At The Lower Layers; However, Only With The Clusters Correspond With The Winner Cluster Determined At 0.0015 Seconds.

4. Hierarchical Nested Dynamic Clustering

We Structure A Hierarchically Nested Dynamically Data Cluster In Which Data At A Higher Layer Are Each Used To Represent Multiple Data At A Lower Layer. Such Structure Allows Us To Search Through A Large Collections Or Groups Of Digital Images More Effectively. Furthermore, Due To Dynamic And Non-Stationary Nature Of The Problem Implementing Traditional Approach With Pre-Defined Parameters And Fixed Structures Does Not Seem Practical; Therefore, We Need Dynamically Evolving As Well As Recursive Algorithm To Form The Data Clusters.

Developed A Hierarchical Annular Histogram (Hah) And Tested It On Images From Prostate Cancer. They Consider The Hierarchy Of Image To Sub-Images And Not A Hierarchy Of Nested Clusters/Image Clouds As In The Proposed Paper And Applied Their Technique To A Small Amount Of Images From A Specific Area Only. On The Other Hand, They Applied A Hierarchical Entropy-Based Representation (Her) To A Database Containing Several Shapes Represented By Their Closest Contour In Curvilinear Coordinates To Be Used In A Cbir System. A Tree-Based Structure Of Representation Of Images Was Proposed, Where A Root Node Contains The Global

Features, As Opposed To Child Nodes Which Contain The Local Features. Authors Also Used Multi-Layer Self-Organizing Map To Form The Tree Structure. In A Multi-Level Hierarchy Was Proposed And Applied To Text Retrieval And Natural Language. Finally, In A Hierarchical Structure To Which Dynamic Indexing And Guided Search Are Applied Using Wavelet-Based Scheme For Multiple Features Extracted From Images In A Warehouse.

We Offer A Hierarchy Of Nested Clusters Of Mean Values, Not Images And Sub-Images Or Features. Last, But Not Least, It Is Important To Select Appropriate Proximity And Similarity Measure Used For Clustering And Search. Traditionally, Euclidean, Mahalonobis, Cosine, Manhattan/City Distance Measures Are Used. We Use Relative Manhattan (L1) Distance.

4.1 Image Representation
Alexnet Is A Convolutional Neural Network That Rose To Prominence When It Won The Imagenet Large Scale Visual Recognition Challenge (Ilsvrc), Which Is An Annual Challenge That Evaluates Algorithms For Object Detection And Image Classification At Large Scale Used For Represent The Image In A Database In Hierarchical Nested Dynamic.

Important In The Design Of Alexnet Was A Suite Of Methods That Were New Or Successful, But Not Widely Adopted At The Time. Now, They Have Become Requirements When Using Cnns For Image Representation.

4.2 Image Indexing
The Hierarchy Nested Dynamic Builds Automatically A Dynamically Evolving Hierarchically Nested Image Clusters Structure From Unstructured Big Data Streams Facilitating The Search Of Most Relevant Similar Images Using Local Density. From The Computing Realization Point Of View, The Proposed Method Can Be Realized As A Client-Server System Which Can Be Offered As A Web Service. Maximum Local Density Indicates The Image Clusters With Mean Values Or Images. Going Down Through The Levels Of The Hierarchy, A Cluster With A Reasonably Small Number Of Visually Similar Images Can Be Identified For A Very Small Amount Of Time From A Big Image Stream. It Works With Vectors Of Multi-Features And Means And Accumulated Scalar Products. It Is Not Using Pixels Directly.

4.3 Image Retrieval
After Forming The Nested Dynamic Cluster And The Hierarchical Structure Is To Find The Cluster Which Contains The Most Similar Images To The Query. In Order To Do That, We Use Local Recursive Density Estimation, Rde. An Alternative Is The Recently Introduced Typicality Measure. Both Of Them Give An Estimate Of The Similarity Between The Query And All Images From The Dynamic Clusters, Such A Recursive Technique Makes Possible That Each Image Is Considered Only Once And Discarded Once It Has Been Processed And Not Kept In The Memory, But The Information Is Still Exact.

4.4 Execution Time
The Execution Time With Hierarchy Of Nested Clusters Was Tested Onseveral Randomly Selected Queries And Compared. The Comparison Starts At The Top Layer First And Continuous At The Lower Layers; However, Only With The Clusters Correspond With The Winner Cluster Determined At The Layer Was 0.0013.

4.5 Comparison Analysis
We Compare The Various Hierarchies With Specified Parameters Like Image Representation, Image Indexing, Image Retrieval And Execution.

S.No.	Parameters	Hierarchical Clustering	Hierarchical Nested Clustering	Hierarchical Nested Dynamic Clustering
1	Image Representation	Alexnet	Alexnet	Alexnet
2	Image Indexing	Euclidean Distance	Recursive Similarity Based Learning	Evolving Local Mean
3	Image Retrieval	Similarity Measure	Local Density Estimation	Recursive Density Estimation
4	Execution Time	0.0017	0.0015	0.0013

5. Results And Discussion

The Proposed Approach Was Tested With A Dataset Of 30,000 Images Collected Within The Cifar Database. Once The Winning Cluster At The Lowest Layers (Layer 1) Is Selected, The Images Inside The Cluster Is Re-Arranged Based On Their Similarity To The Query Image Using Self Organization Map. Small Distance Implies That The Corresponding Image Is More Similar To The Query Image And Vice Versa.The Execution Time Of The Proposed Approach With Hierarchy Of Nested Clusters Was Tested Onseveral Randomly Selected Queries And Compared With (I) No Clustering Or Hierarchical Structure And Direct Comparison Of The Query Image With Each Of 30,000 Images (Ii) Plain Clustering With No Hierarchical Nested Structure. The Execution Time Of The Hierarchical Clustering Approach Was 0.0017 Seconds, The Execution Time Of The Hierarchy Of Nested Clusters Was 0.0015 Seconds, The Execution Time With Hierarchy Of Nested Clusters Was 0.0013

Methods	**Execution Time (S)**
Hierarchical Clustering	0.0017
Hierarchical Nested Clustering	0.0015
Hierarchical Nested Dynamic Clustering	0.0013

Table-1: Execution Time Compare With Different Clusters Setup

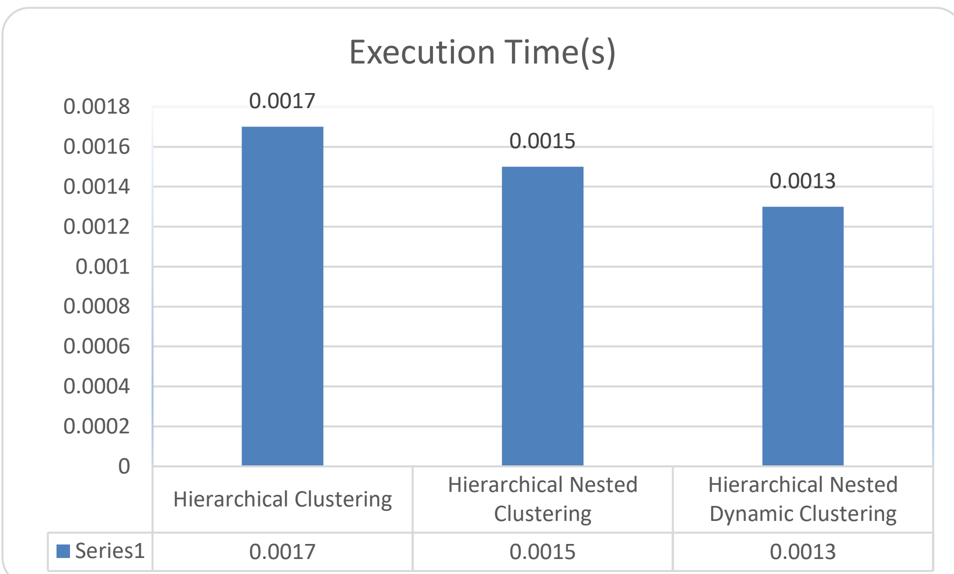

Figure-1: Execution Time Compare With Different Clusters Setup

In This Experiment, The Hierarchical System Is Made In Two Layers; However, The Approach Is Scalable; Thus, More Layers Can Be Integrated If Necessary. Nested Clustering Was Used To Form The Hierarchical Nested Clusters. At The Lower Layer All 30,000 Images Were Grouped Into 10 Major Clusters While At The Higher Layer It Reduced To 30 Clusters. In This Experiment, The Extracted Features From Convolutional Neural Network(Cnn) Are Used To Form The Clusters And To Assign The Indices Of The Particular Images. The 10,000 Images Were Trained By Cnn For Identifying Their Statistical Features. Agglomerative Algorithm Was Applied To The Mean Values Of Extracted Features Of The Images.

6. Conclusion

These Algorithmsare New Fast Approach For Organization Of Hierarchical With Nested Dynamic Cluster And Search Within Cbir Context Has More Accurate. These Approach Were Tested On A Data Base Which Contains 10,000 Images From About 10 Different Genres/Rubrics. The Proposed Algorithm Was Able To Automatically

Form 9417 Visually Very Relevant Results Within Few Milliseconds Making Only About Simple Calculations. The Obtained Accuracy Is 94.17%. The Approach Is Scalable And Parallelizable In Nature. It Can Be Realized As A Web Service. It Is Also Possible To Include User Feedback In A Future Application.

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