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ORIGINAL RESEARCH

Construction Models for Image Sketching and Retrieval: A Systematic Review

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Abstract:

Introduction: Image searching is a continual challenge even with the many image retrieval models that have sprung up. Sketch-Based Image Retrieval (SBIR) models attempt to solve this challenge by searching using sketching. The existing SBIR algorithms have limited performance because of ambiguities and variations in hand-drawn sketches.

Aims: The aim of this work was to review and identify the strengths and weaknesses of the existing SBIR models.

Materials and Methods: Articles were selected from Google Scholar assessing strictly sketch construction models. Search terms include sketch construction, sketch-based image retrieval, hypermedia, multimedia, design strategies, and algorithms.

Results: The search returned 455 articles of which only 134 studies met the inclusion criteria. 30 papers were on Convolutional Neural Network (CNN) and hybrids. 6 on Contour and Stroke Segments. 4 on Generative Adversarial Network while 3 papers were on Deep Hashing. 6 papers reported use of 3D-CNN-based methods while 85 papers used other methods like sparse coding and bag of regions. Accuracy, recall and precision ranged from 59.47% to 99.4%, 20.10% to 47.70% and 33.40% to 51.00% respectively.

Conclusion: There are some promising SBIR models but lots of effort is required if computational SBIRs are to be adopted. Most studies did not include any performance metric which makes it difficult to assess the performances of the algorithms proposed. Researchers are advised to always report the performance algorithms. The future plan is to develop a robust SBIR algorithm which will accommodate handwriting ambiguity variations.

Keywords: Image sketching, image Retrieval, Hypermedia, Multimedia, Image Construction.

All co-authors agreed to have their names listed as authors.

1. INTRODUCTION

As the proliferation of image capturing devices has continued to increase exponentially, so also is the number of images in the multimedia space. Unlike text-based searches, searching for images has continued to be a challenge even with the many models that have sprung up over the years [1-3]. Sketch-Based Image Retrieval (SBIR) models attempt to solve this challenge by allowing users to draw or sketch the images they intend to search and the search engine in turn, retrieves all relevant images. Multimedia data are of high dimensions and are huge. Also, the importance and applications of multimedia data plus the ever-increasing activities on social media has led to an exponential growth of the multimedia space. These make image retrieval especially when they are untagged, time-consuming, tasking, and cumbersome [4-6].

There are increasing research efforts on the development of image retrieval models targeted at improving performance and creation of smart models for retrieval of images and multimedia files.

Image retrieval algorithms can be grouped into different categories, for example, the Fine-Grained SBIR (FG-SBIR), Zero-Shot SBIR (ZS-SBIR) and Low-Shot SBIR (Figure (1)). Fine-Grained requires user intervention because it relies on specific photo instance given a free-hand sketch input [7]. On the contrary, the zero-shot retrieves images even without prior sketch from the user [8, 9]. Zero-Shot is commonly used in real-life scenarios, unlike traditional SBIR methods that assume that both the training and testing classes share the same categories, which in real-life, is inapplicable [10]. Low-Shot on the other hand, retrieves images using hand-drawn sketch queries that are rarely seen during the training phase [11].

For the Zero-Shot SBIR, at retrieval time, sketches can be gotten from novel classes, that were not present at training time using the Inverse auto-regressive flow-based variational auto-encoder for zero-based SBIR [12]. Likewise, Norm-guided adaptive visual embedding (NAVE) for ZS-SBIR builds the common embedding based on visual similarity rather than language-based pre-defined prototypes [13]. Another is the Three-Way Vision Transformer (TVT) method which is also a Zero-Shot Sketch-Based Image Retrieval (ZS-SBIR) system that retrieves natural images related to sketch queries from unseen categories. It operates through the Multi-Modal Hypersphere Learning [9].

In Fine-Grained SBIR model, the multi-stream encoder-decoder model was used to guide representation of the vector space of the current sketch to approximate that of its later sketches. This helps to realize the retrieval performance of the sketch with fewer strokes to that of the sketch with more strokes [14]. A triplet homogeneous network was first used to solve the Fine-Grained Color SBIR (CSBIR) problem using a novel ranking method based on multi-branch deep convolutional neural networks that considered both shape matching and color matching [15]. Also, a novel network that is capable of cultivating sketch-specific hierarchies and exploiting them was designed to match sketch with photo at corresponding hierarchical levels also for fine-grained SBIR [16].

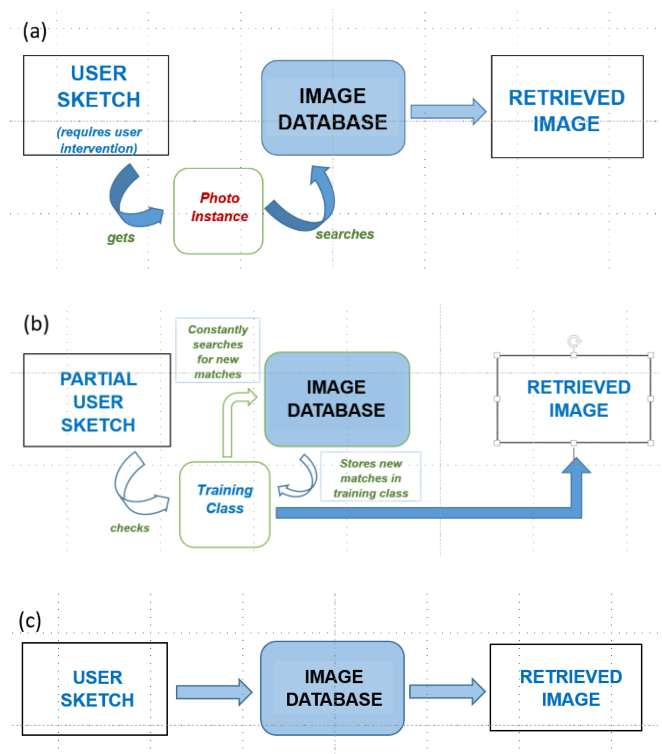

Figure 1: (a), (b) and (c) represent the search flow for FG-SBIR, ZS-SBIR and Low-Shot SBIR systems respectively

Some older methods however purely detect local features via densely sampled stroke points and

explained by quantized histogram of gradients interpolated by Poisson equation [17]. Fuzzy C-means for clustering, wavelet Transform for denoising, wavelet transform for image processing and indexing was done by the Lucene Algorithm [18]. While some newer ones first transform the sketch and photo into the same domain before actual comparisons starts [19, 20], others generates complex and creative sketches form images that are later used for corresponding image matching purposes [21].
All with the aim of devising the best methodology that can effectively search out images via sketches as input queries.
Unfortunately, the existing sketch-based image retrieval algorithms have limited performance because of ambiguities and variations in hand-drawn sketches. Issues such as cross-domain incompatibility, class imbalance, invariance in rotation, translation and scale, invariance to similarity transformations, spatial deformations exists [4, 22-27]. The problems associated with these sketch-based image retrieval models are currently attracting a lot of research efforts because of the importance of images in this technology-driven world. This has spurred the reason for this work. The goal of this study was to review the existing image retrieval models, identify their strengths and weaknesses, and recommend possible improvements.

2. MATERIAL AND METHODS

The review was conducted using the Systematic Literature Review steps [28, 29]. These include study design, search strategy and information sources; study selection and data collection process; and quality assessment and data synthesis.

2.1 Study Design, Search Strategy and Information Sources

A systematic review was carried out on sketch construction for sketch based image retrieval studies that met a priori defined inclusion and exclusion criteria. Search strategy used is composed as follows: (a) Construction of search terms by major keywords identification (b) Determination of synonyms or alternate words for the major keywords; (c) Establishing exclusion criteria to make exclusion in the course of search and (d) Application of Boolean operators in the construction of required search terms.

Results for (a): Sketch, Image, Retrieval, Dataset, Hypermedia, Multimedia, Construction.

Results for (b): sketch construction AND "sketch based image retrieval" hypermedia OR multimedia OR "design strategies" OR algorithms "sketch based image retrieval"

Results of (c): -video -audio

Results for (d): sketch construction | "sketch based image retrieval" | hypermedia | multimedia | "design strategies" | algorithms | "sketch based image retrieval" -video -audio

Searches were conducted in Google Scholar database which comprises of peer-reviewed articles. Construction models for image sketching and retrieval were strictly searched for using the search term constructed as in "Results for (d)" above – and this became the final search term arrived at for this research work. The resources returned by the searches fall into different publication categories, e.g. dissertations, theses, journals, research proposals, conference proceedings, articles and book chapters.

2.1.1 Study Selection and Data Collection Process

To present the study selection process, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [15] was adopted. This established the studies included and those excluded for this research. The study selection process is represented in Figure (2) in the PRISMA flow diagram.

Considerations were based on studies involving sketch-based image retrieval and sketch construction models only. Restrictions on the study was on sketch based image retrieval as applied to sketch construction. Thus, the usage of the search terms: sketch construction AND sketch based image retrieval, hypermedia, multimedia, design strategies and algorithms.

2.1.2 Exclusion criteria

Studies were excluded if they are based on the following:
a. Irrelevant study design

b. Incomplete study design
c. Inappropriate study design
d. No information on outcomes of interest

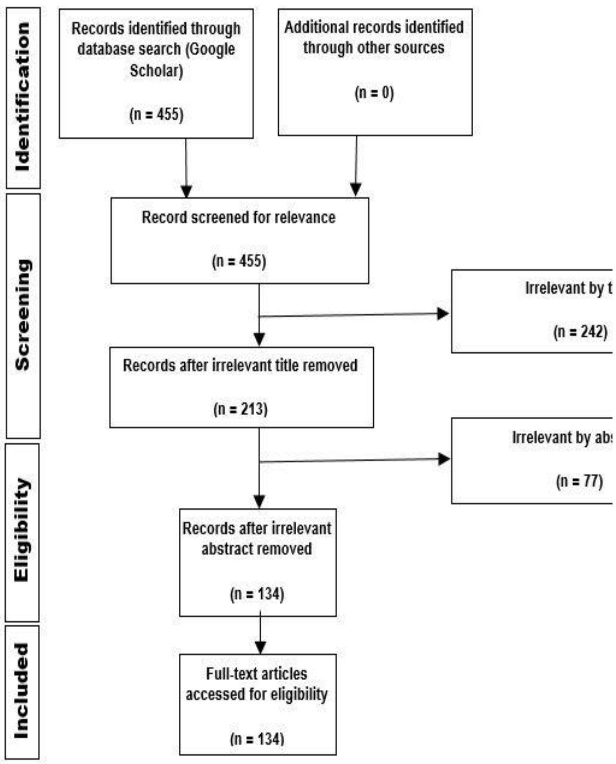

Figure 2: Flow Diagram for Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) of included studies

2.1.3 Selecting Primary Sources

Primary sources were initially selected based on the identification of the results of various studies. These studies were based on both the search term and the inclusion of one or more elements of the keywords that is related to the work in any way. The publication assessment quality was also a criterion on which selection was made and in other to minimize bias, the following was put into consideration; If the algorithm are for sketch-based image retrieval and construction; If the image retrieval method was sketch based; If the algorithm for sketch-based image retrieval is clearly computational; If the retrieval method was specifically for multimedia files; If design strategies for image retrieval via sketch was computational and well spelt out; If algorithm has elements of sketch construction of missing image parts; Title of studies and abstracts were also bases on which selection was made.

The data extracted from each publication are the: title, author, year, country of lead author, reference, algorithm/method (methodology), strengths, weaknesses/limitations, programming language, dataset, publication quality, description and year. Categorization of collected data gotten from the final publication sample was based on some performance metrics.

In other to derive a list of categories to help in the classification of the performance metrics, a thorough review was done. Eleven (11) categories were initially identified; this was further merged to seven (7) major ones as presented in section 3.1.
As selection approached final stage, full texts of the finally selected papers were thoroughly read and analyzed.

3. RESULTS

As presented in Figure 2, 455 potentially relevant studies were identified using the final search term as stated in 2.1. Titles were reviewed using the exclusion criteria and that led to the exclusion of 242 studies. The abstracts of the remaining 213 articles were then reviewed and 77 irrelevant ones were removed, reducing the eligible articles to 134.

We observed that out of the 134 papers, 43 were published in China, 26 in the UK, 19 in India and 14 in the USA. Others are from different countries, but not a single one from Nigeria or Africa.

We further observed that the algorithms used can be broadly classified into six (6) groups based on methodology. The grouping was done based on the several distinct methodologies that was used to solve the eminent limitations in the study. Note that these algorithms were used across the fine-grained, zero-shot and low-shot categories. These are Convolutional Neural Network (CNN), Contour & Stroke Segments, Generative Adversarial Networks (GAN), Deep Hashing & Hashing, CNN Methods for 3D Shapes and Hybrid Models & Others.
CNN models are trained and then reused based on previous results to predict the outcome of a process. In this case, based on user results and feedback, the convolutional network is continuously trained to predict images via user sketches. Contour and Stroke Segments however stores edges and lines of sketches in datasets and can predict the corresponding

images, this also gets better as more and more contours are stored on acceptable user feedbacks. GAN are used to generate sketches from images. These sketches are also stored to make future predictions easier. Hashing algorithms generate intelligent indexes that can predict the unknown behavior of the image patches, sketches, contours or edges. CNN methods for 3D shapes uses CNN models in the 3-Dimensional and uses advanced deep learning for the retrieval of 3D models via 3D sketches. A hybrid models uses more than one existing models to develop a new one. Other models are the ones that appear only once or are incomplete or under development.

Out of the 134 research, thirty (30) studies explicitly focused on Convolutional Neural Network methods. Six (6) implicitly focused on sketch strokes and image contour detection algorithms. Table (1) contains the grouping of all the studies based on the methods used.

Table 1: Image Retrieval and Construction Studies grouped based on their Algorithms

Computational Model	**Number of Studies**	**Studies**
Convolutional Neural Network	30	[10, 11, 13, 16, 20, 27, 30-53]
Contour & Stroke Segments	6	[17, 54-58]
Generative Adversarial Networks	4	[59-62]
Deep Hashing & Hashing	3	[8, 63, 64]
CNN Methods for 3D Shapes	6	[65-70]
Hybrid Models & Others	85	[1-7, 9, 12, 17, 18, 22-24, 26, 70-138]

3.1 Strengths and Weaknesses of existing Models and Techniques

The following lists the strengths and weaknesses of various algorithms on sketch construction [20, 53, 55, 59, 70].

3.1.1 Convolutional Neural Network

CNN models uses neural networks inspired by the human brain for training. These models become intelligent with time due to feedbacks from users.
Strengths: User sketches are analyzed on-the-fly and as such, photos are instantly retrieved.
Weaknesses: It was observed that it was not yet tested with incremental learning and dealing with the ambiguity of the hand-drawn sketches still exists. Also, some sketches cannot be transformed into ideal photos. Most algorithms needs to be unsupervised at all level and not only at the category level.
Datasets: Sketch-oriented augmented dataset, Sketchy [59], TU-Berlin [30, 53], COCO

3.1.2 Contour & Stroke Segments

These models extracts, stores and trains contours, edges and stroke segments from images and sketches respectively.
Strengths: It allows for local features to be detected via densely sampled stroke points. Also, searching of target images with similarities to the contour query is possible. Images with simple background can be found via sketch inputs.
Weaknesses: Issues with deformed strokes and contours exists in some models and model was not able to recognize and process these stokes.

Datasets: TU-Berlin [8]. A database of 1.3 million images.

3.1.3 Generative Adversarial Networks

This allows for generation of images from sketches and vice-versa.
Strengths: It gives a boost to the resolution of an image. For sketch to image interpretation, a new image can be generated from a sketch with the help of a GAN model.
Weaknesses: There is need to reduce processing time.
Dataset: TU-Berlin, Sketchy.

3.1.4 Deep Hashing & Hashing

These methods learn a group of hash functions to map original data into compact binary codes. This at the same time preserves some notion of similarity in the Hamming or mathematical space. The corresponding generated binary codes are effective for image retrieval and highly efficient for large-scale data storage.
Strengths: It has low storage consumption and fast retrieval speed. It allows for inter-domain cross-modal searches between sketches and images and the encoding of free-hand sketches with natural images.
Weaknesses: There is need to run on larger datasets unsupervised.
Dataset: Sketchy Extended, TU-Berlin Extended.

3.1.5 CNN Methods for 3D Shapes

This employs the usage of advanced deep learning for the retrieval of 3D models via 3D sketches. 3D CNNs uses 3D convolutional kernels to make segmentation predictions for a volumetric patch of a scan of the image that is being searched for.
Strengths: The images becomes scalable in the spatial direction, allowing accurate image detection with different frame sizes.
Weaknesses: Larger collection of 3D sketches are needed for training purposes.
Dataset: SHREC13STB [65].

3.1.6 Hybrid Models & Others

Hybrid models utilizes and combines the strengths of more than one model to produce newer ones. While other models appear just once or are still under development. There are also papers that reviewed and reported several models.
Strengths: Enhances the performance of the retrieval model in terms of increased efficiency, leading to better accuracy.
Weaknesses: Some hybrid models consume processor time. Some takes longer to run on large datasets.
Datasets: ETH, Sketchy, TU-Berlin, QuickDraw [9], a large social image dataset containing 100,000 images from Flickr.

3.2. Performance Metrics for Sketch Construction and Image Retrieval

Performance measurement was based on the following three (3) identified measures: Accuracy, Recall and Precision.
Accuracy ranged from 59.47% (0.5947) to 99.4% (0.994), the range of Recall was from 0.201 to 0.4772 and Precision spanned 0.334 to 0.510.

4. DISCUSSION

In this study, we reviewed the existing studies on sketch based image retrieval. We observed that there are a lot of research efforts in this interesting topic, but all are from the developed world with very few from the developing world. Unfortunately, there is no single study from Nigeria. This is not very good because Nigeria is the most populated country in Africa and the economy is fast growing. Also, most companies in Nigeria have adopted ICT and many internet users are interested in searching for images on the internet.
We also found that the methods used in the existing studies can be grouped into 6 categories based on the algorithms used. These are the Convolutional Neural Network, Contour & Stroke Segments, Generative Adversarial Networks, Deep Hashing & Hashing, CNN Methods for 3D Shapes and Hybrid Models & Others. We found that most of the studies used CNN.
From our studies, CNN was proffered most and this might be because of the ability to learn, relearn and predict results which makes the model more robust and intelligent in the long run. Meanwhile, the contour and stroke segment models could also work great if widely embraced. This is because it has the ability to store segments of images and corresponding sketches with algorithms that can easily predict seen occurrences via keystrokes. From result, Nigeria been an African country and one that has a very high social media engagement has no paper and this could be as a result of the researchers not coming to the reality of the possibility of retrieving the high volume of multimedia content that are posted online on a daily basis. This reality however is scary and already an ongong problem

as there are difficulties already retrieving multimedia files from the clouds. Hence, the inability of researchers to get adequate support from research bodies, also inadequate access to internet facilities and constant electricity, and most importantly, not incorporating appropriate technological stacks and programming languages to the undergraduate curriculum are reasons why no paper was recorded.

We observed that accuracy and recall were the most commonly reported performance metrics. Accuracy is a very important performance metric and should be reported by researchers. We hereby recommend that future works on information retrieval should report precision, recall and accuracy.

The major strength of our study is that we used a standard method to conduct the systematic review. We used PRISMA which has been recommended as the best systematic review guideline. Also, we grouped all existing algorithms based on their theoretical background and modus operandi. We also identified the strengths and weaknesses of each category. This will help other researchers to easily identify which method is good for their use cases.

Our study has some limitations. The first one is the use of only one database, Google Scholar for search. We used Google scholar because it is free and the mostly used database worldwide. Other databases are commercial and need subscription which we cannot afford for now because of funding constraints. It could be argued that the use of a single database could make us to miss some articles. This is actually not the case, because google scholar also fetches resources from other commercial databases, although, it may not give access to the full texts. In our case, we had access to all materials retrieved from google scholar. So, the chance of missing important article is small.

5. CONCLUSION

In conclusion, a systematic review was carried out in other to examine and analyze existing methods that are used in retrieving images and the average recall as regards the retrieval and generation of sketches as used on various platforms is still not very high. We found that there is no single published work on this topic in Nigeria. We also found that CNN is the most widely used method. We hereby recommend that researchers should consider working in this area of research. We also recommend that probability or statistical based method should be considered in future studies. Also, personalization and adaptability of sketch-based image retrieval methods in the hypermedia layer should be looked at.

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COMPETING INTERESTS

The authors declare that there are no competing interests.

AUTHORS' CONTRIBUTIONS

Oluwabunmi Joycey Omole conducted literature search, analysed published works and wrote the first draft of the manuscript. Oluwatoyin Enikuomehin and Benjamin Aribisala designed the study, revised the manuscript, wrote the final copy of the manuscript and supervised the study.

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