A Color Quantization Optimization Approach for Image Representation Learning

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Abstract Over the last two decades, hand-crafted feature extractors have been used in order to compose image representations. Recently, data-driven feature learning have been explored as a way of producing more representative visual features. In this work, we proposed two approaches to learn image visual representations which aims at providing more effective and compact image representations. Our strategy employs Genetic Algorithms to improve hand-crafted feature extraction algorithms by optimizing colour quantization for the image domain. Our hypothesis is that changes in the quantization affect the description quality of the features enabling representation improvements. We conducted a series of experiments in order to evaluate the robustness of the proposed approaches in the task of content-based image retrieval in eight well-known datasets from different visual properties. Experimental results indicated that the approach focused on representation effectiveness outperformed the baselines in all the tested scenarios. The other approach, more focused on compactness, was able to produce competitive results by keeping or even reducing the final feature dimensionality until 25% smaller with statistically equivalent performance.

Keywords representation learning · color quantization · CBIR · genetic algorithm · feature extraction

1 Introduction

It is known that the form in which data is represented can highly influence the performance of machine learning methods in visual pattern recognition tasks, such as Content-Based Image Retrieval [28], Object Detection [35], Remote
Sensing [6] and Image Classification [14]. In the last years, Representation Learning [1], which consists on the process of using pattern recognition algorithms to find representations optimized for a given data domain and/or task at focus, has become a tendency.

The current state-of-art methods for representation learning, which are based on Deep Learning [11] techniques, in many cases present a considerable gain in description effectiveness. However, the use of these methods presents serious drawbacks, such as the difficulties in properly exploring its range of parameters and possible architectures, the superior computational time spent its training and the big amount of data required to produce efficient learning models, leaving space for alternatives.

Existing methodologies for visual representation learning can be classified into two main approaches: those that learn representations from a feature set provided by a hand-crafted extractor and those that completely compose new ones without any prior feature extraction (from scratch). Following the later approach, complex multi-layered learning processes as the ones executed by Deep Neural Networks are not always needed in order to produce representative features. Depending on the scenario, the improvement of existent representations is already enough to fairly solve the task.

Few years ago, before the arising of Deep Neural Networks, hand-crafted feature extractors were used in order to compose image representations [14, 25, 21]. Among them, the Border Interior Classification (BIC) [30] achieved prominent results, being in several cases more effective than its competitors [17, 20] and also faster at computing representations. This behaviour states BIC features as promising candidates for undergoing a feature leaning process and providing better results.

Examining the extraction procedure of this method, a fact comes to observation: it uses a fixed RGB colour-space uniformly quantized in 4 tonalities for each axis. According to Stehling et. al [29], this configuration was chosen due the achievement of good results in a majority of tested scenarios and the compatibility with other feature extraction methods which rely on the same colour scheme. However, it raises the question whether a different quantization could provide better representations.

The use of a different colour quantization, specially one adapted to the current image domain instead of a predefined one, could allow the enhancement of convenient image features and the suppression of others. Since the representations are based on colour histograms, the enhancement and detailing of colours that favour the closeness of similar images and the distinction of different ones, according to the task criteria, would provide the composition of more representative features and, consequently, improvements on the task performance. Furthermore, a domain-oriented quantization allows the discard of the less contributing tonalities resulting in a possible reduction of the representation size.

This work proposes an approach of representation learning in order to improve the description effectiveness of an existent feature extractor by exploring a particular characteristic of the current image context, its colour distribution.
Our hypothesis is that changing the colour quantization affects the description quality of the features in the sense that a tonality configuration optimized for a given domain could produce more effective and compact image representations.

2 Related Work

In the last decade, several feature learning techniques were developed for raw image data [9, 32, 25, 12, 3, 2, 36]. Approaches regarding deep belief nets [9], denoising autoencoders [32], deep Boltzmann machines [25], convolutional deep belief networks [12], K-Means based feature learning [3], hierarchical matching pursuit [2] and sparse coding [36] address this purpose.

Some works developed quantization learning using evolutive heuristics for Image Segmentation [15]. Scheunders [27] treats the quantization problem as global image segmentation and proposes an optimal mean squared quantizer and a hybrid technique combining optimal quantization with a Genetic Algorithm modelling [8]. Further, the same author [27] presents a genetic c-means clustering algorithm (GCMA), which is a hybrid technique combining the c-means clustering algorithm (CMA) with Genetic Algorithm. Lastly, Omran et al. [18] developed colour image quantization algorithm based on a combination of Particle Swarm Optimization (PSO) and K-means clustering.

Regarding the effects of colour quantization changing on image representations, Ponti et al. [22] approached the colour quantization procedure as a pre-processing step of feature extraction. They applied four fixed quantization methods - Gleam, Intensity, Luminance and a concatenation of the Most Significant Bits (MSB) - over the images of three datasets and then used four feature extractors - ACC, BIC, CCV and Haralick-6 - to compute representations intended to solve the tasks of Image Classification and Image Retrieval. Their conclusions show that it is possible to obtain compact and effective feature vectors by extracting features from images with reduced pixel depth and how the feature extraction and dimensionality reduction are affected by different quantization methods.

3 Background

3.1 Color Quantization-based Feature Extraction Algorithms

Border/Interior Classification. Stehling et al. [30] proposed BIC, a simple and fast approach for feature extraction which presented prominent results in web image retrieval [19] and remote sensing image classification [26, 17]. This approach relies on a RGB colour-space uniformly quantized in $4 \times 4 \times 4 = 64$ colours. After the quantization, it applies a segmentation procedure, which classifies the image pixels according to a neighborhood criterion: a pixel is classified as interior if its 4-neighbours (right, left, top, and bottom) have the
same quantized color; otherwise, it is classified as border. Then, two color histograms, one for border pixels and other for interior pixels, are computed and concatenated composing a 128-bins representation. At the end, the histograms undergo two normalizations: division by the maximum value, for image dimension invariance, and a transformation according to a discrete logarithmic function, aiming to smooth major discrepancies.

*Global Color Histogram.* GCH [31] is a widely used feature extractor which presents one of the simplest forms of encoding image information in a representation, a color histogram, which is basically the computation of the pixel frequencies of each color. It relies on the same uniformly quantized RGB color-space such as BIC and, consequently, produces a feature vector of 64 bins. After the histogram computation, it undergoes a normalization by the max value in order to avoid scaling bias.

### 3.2 Genetic Algorithm

GA is a bio-inspired optimization heuristic that mimics natural genetic evolution to search the optimal in a solution space [8]. It models potential solutions for the problem as individuals of a population and subject them to a iterative process of combinations and transformations towards an improved population.

At each step, GA randomly selects individuals from the current population, called parents, and exchange its parts in order to produce the next generation in a operation called cross-over. Some individuals are also selected to undergo a mutation operation, which consist on randomly changing small pieces of the individual, also integrate the new generation [5]. When a new generation is formed, its individuals are evaluated by a fitness function, whose the result provides the individual performance on the current problem. According to this function score, the algorithm selects the parent individuals that will generate the next population, simulating a natural selection. At the end of the process, when the stopping condition be satisfied, the expected result is the individual which encodes the best solution as possible.

### 4 Methodology

The present method employs Genetic Algorithm in order to learn quantized color optimization for the given image domain. Figure 1 illustrate an overview of the entire process, which is composed by two main steps: (1) quantization learning and (2) image description. These steps are better described next.

In our modelling, a quantization is represented in an GA individual by the following manner. The individual takes reference from the widest possible quantization, presented in Figure 2 and aggregates its intervals according to the configuration specified by the respective individual as it is detailed in Figure 3.
Fig. 1: Overview of the proposed approach. First, we use Genetic Algorithm to search an optimized color quantization, then the resultant configuration is incorporated in the feature extractor to generate improved image representations.

4.1 Quantization Learning

In order to find a quantization that would provide a superior power of description and compactness for the image representations generated for a given image context, we opted by perform an optimization process provided by the Genetic Algorithm [8]. It provides a fairly chance of reaching a global optimum by starting with multiple random search points and considering several candidate solutions simultaneously. Consequently, it represents a fair alternative to an exhaustive search strategy, which would be infeasible given the amount of possible quantization.

According to this optimization algorithm, an individual corresponds to a representation of a potential solution to the problem that is being analysed. In
Fig. 3: Our modelling implements each individual as a binary array, being one value for each color tonality interval. If a interval has its respective bit as set, it has its own position in the produced quantization, otherwise, it is aggregated to the immediate previous interval.

Algorithm 1 illustrates the proposed GA-based quantization. The population starts with individuals created randomly (line 4). The population evolution starts generation by generation through genetic operations (line 5). A function is used to assign the fitness value for each individual (lines 6-7). The best individuals in each generation are recorded (lines 9-10). Then, genetic operators are applied to evolve this population (line 11). The last step is to select the best individual $q^*$ along all generations (line 13). The individual
q* will be used to define the quantization used in the feature representation process.

4.2 Image Description

On the second phase, the learnt individual quantization q* is used with the feature extractor algorithm to produce color image representation. In order to do that, it was necessary to implement a slightly modified version of the feature extractor, that incorporates the capacity of generating representations according to a specified color quantization. The equations 1, 2 and 3, where N is the maximum color axis size and q* the quantization individual, show how to calculate the new R, G and B values for each pixel.

\[
R_{new} = \left( \sum_{i=0}^{r} q^*[i] \right) \times \frac{|R_{axis}|}{256}, \quad \text{where } r = R \times \frac{N}{256}; \quad |R_{axis}| = \sum_{i=0}^{N} q^*[i] \quad (1)
\]

\[
G_{new} = \left( \sum_{j=N}^{g+N} q^*[i] \right) \times \frac{|G_{axis}|}{256}, \quad \text{where } g = G \times \frac{N}{256}; \quad |G_{axis}| = \sum_{m=N}^{2N} q^*[m] \quad (2)
\]

\[
B_{new} = \left( \sum_{k=2N}^{b+2N} q^*[i] \right) \times \frac{|B_{axis}|}{256}, \quad \text{where } b = B \times \frac{N}{256}; \quad |B_{axis}| = \sum_{n=2N}^{3N} q^*[n] \quad (3)
\]

5 Experimental Setup

In order to verify our colour quantization hypothesis and evaluate the proposed method approaches, we conducted experiments using eight different image datasets. The details about the experiments setup are presented as follows.

5.1 Task

Although the discriminative property of the method produced representations make them suitable to be used in variety of pattern recognition tasks, such as Image Classification [26] and Image Retrieval [19], we opted by evaluate the method on the task of Content-Based Image Retrieval (CBIR) [28]. This task can be briefly described as retrieving the most similar images, according to a semantic criteria, to a given query image.

The chosen process intended to evaluate this task consists on describing the whole image set, computing one similarity ranking by Manhattan Distance (L1) for each image against the rest and measuring the overall ranking quality. For this measurement, the image class is adopted as similarity criteria. Consequently, as many images of the same class of the image in comparison remains at the top, better is the ranking.
5.2 Datasets

The experiments were executed over a set of 8 image datasets presented on Table 1. The first two were initially created for Remote Sensing purposes, and the remaining are intended for tasks of general CBIR and Image Classification. Figures 4, 11, 6, 7, 8, 9 and 10 respectively, show samples of these datasets.

| Dataset                        | # of samples | # of classes |
|--------------------------------|--------------|--------------|
| UC Merced Land-use [34]         | 2,100        | 21           |
| Brazilian Coffee Scenes [29]    | 2,876        | 2            |
| Coil-100 [15]                  | 7,200        | 100          |
| Corel-1566 [33]                | 1,566        | 43           |
| Corel-3906 [33]                | 3,906        | 85           |
| ETH-80 [13]                    | 3,280        | 80           |
| MSRCORID [4]                   | 4,320        | 20           |
| Tropical Fruits and Vegetables [23] | 4,960     | 15           |

Fig. 4: Examples of the UC Merced Land-use dataset.
(a) Object 13  (b) Object 14
(c) Object 87  (d) Object 81
Fig. 5: Examples of the COIL-100 dataset.

(a) A6140  (b) A14935  (c) A2231
(d) A0908  (e) A7840  (f) A0004  (g) A12147
Fig. 6: Examples of the COREL 1566 dataset.

(a) A0628  (b) A1401  (c) A4604
(d) A4932  (e) A4932  (f) A7601
Fig. 7: Examples of the COREL 3906 dataset.
Fig. 8: Examples of the ETH-80 dataset.

Fig. 9: Examples of the MSRCORID dataset.
5.3 Parameters

For the GA in the quantization learning phase of the method were used the parameters described in Table 2. The reason behind these values choices regarding cross-over, mutation and tournament relies on being the configuration of best results on the majority of tested scenarios. Regarding the specified population size, it indicated sufficient exploration of the solutions space while its increasing provided no significant improvement. The number of population was chosen according to a criteria of maintaining a distance of at least 50 generations from the best result first appearance in order to ensure convergence.

Table 2: Genetic Algorithm Parameters

| Parameter                  | Value |
|----------------------------|-------|
| Two-point Cross-over Probability | 60%   |
| One-point Mutation Probability | 40%   |
| Number of Generations       | 200   |
| Population Size             | 200   |
| Tournament                  | 5     |
| Elitism                     | 1%    |
The fitness function adopted on our GA evolution process was based on FFP4 [7]. This score is defined for a given query image \( q \) as:

\[
FFP4_q = \sum_{i=1}^{\mid D \mid} r_q(d_i) \times k_8 \times k_9
\]

where \( |D| \) is the image dataset; \( r_q(d) \in [0, 1] \) is the relevance score for the image \( d_i \) associated to the query, it being 1 if relevant and 0 otherwise; and \( k_8 \) and \( k_9 \) are two scaling factors adjusted to 7 e 0.982 respectively. The final fitness function is computed as the mean \( FFP4 \) for all images \( q \in D \).

The use of this fitness is motivated by good results observed in previous works ([7], [24]), which apply this measure on similar evolutive approaches that address the same task.

5.4 Baselines

Since our goal is to propose a method capable of producing improved representations from already defined feature extraction, in order to measure the representations performances, the most suitable baselines are the feature extractor themselves, BIC and GCH, committed to the same experimental process although using its original colour quantization.

5.5 Experimental Protocol

In order to evaluate the proposed method, we conducted \( k \)-fold cross-validation. According to this protocol, the dataset is randomly split into \( k \) mutually exclusive samples subset (folds) of approximated size. Then, the \( k - 1 \) subsets are chosen as training set, and the remaining one as test set. To work with all the dataset, the execution is repeated \( k \) times, and each time a different subset (without replacement) is chosen as the current test set and the remaining compose the training set.

We carried out all experiments choosing \( k = 5 \) folds. As a consequence, for each experiment, the method was executed 5 times using 80% of the dataset as training set and 20% as test set.

6 Results and Discussion

We propose two approaches for the described method. The first, named Non-Limited Approach (NLA), is intended to provided a quantization focused on generating representations that have the better performance as possible. The second, named Limited Approach (LA), has the same goal, however it imposes a limitation on the representations size by giving negative fitness for the generated individuals that present dimensions over this limit. As a consequence,
this later approach tends to focus on compactness. The following subsections present and discuss the experimental results and comparison between these two approaches of our method and its baseline.

6.1 Non-limited Approach

Figures 12a and 12b present the performance comparison between NLA and the baselines in the described task. Considering only the mean values of avg. P@10, our method outperforms the baseline. However, due to the proximity of the results, we used the Students Paired t-Test [10] to statistically verify this conclusion. According to the null hypothesis criteria of this test, it is possible to say that our method results outperforms the ones of the baseline in all datasets.

Observing the resultant feature vector dimensions in Figures 14a and 14b, the discrepancy between the two methods is easily noticeable. The representations produced by our method approach are, on average, around 300% bigger than the ones generated by the baseline. The reason for this outcome relies on the fact that the fitness function used for evaluate the genetic algorithm individuals prioritizes the representations performance on the task and does not consider any aspect related to its dimensions. That being said, it is likely that occurred a detailing of the colour tonalities generating a superior number of intervals and resulting in higher dimensions.

![Fig. 12: Comparison between the P@10 results of NLA and the feature extractors.](image-url)
Fig. 13: Comparison between the MAP results of NLA and the feature extractors.

Fig. 14: Comparison between the representation size results of NLA and the feature extractors.

6.2 Limited Approach

The charts of Figures 21 and 22 show a pattern among for all datasets. The performance results of LA were superior than the baseline for limits 64, 96, and 128. However, statistical tests according the Students Paired Method show an overlapping between the results for the limits 96 and 64. Consequently, it is possible to declare that BIC method was outperformed only in cases of limit 128. Furthermore, the ascending behaviour of the performances suggests that as bigger the representation as superior its feature detailing level, which leads to a better representation quality.

The results of Figures 25 and 26 show that the generated quantizations almost exhausted the feature detailing by producing representations that reached
or stayed very close to the dimension upper-bound. This is possibly a consequence of the optimization strategy of the method which is guided by the task performance. A fitness function that also considers the feature vector dimension would likely favour the generation of smaller representations under the same limit.

The presented results prove our hypothesis that it is possible to find a quantization optimized for a given domain that could provide an improved representation effectiveness and compactness. According to Figure 21, the results of limit 128, which present the same representation size as the ones of the BIC extractor, outperformed the retrieval quality of the baseline. Some results of limit 96 were even further presenting better performance with a smaller feature vector leading to conclude the possibility of improvements in performance and compactness simultaneously on the same quantization. Other results of limit 96 and 64 were statically tied with the baseline demonstrating the possibility of a significant reduction of the description size, until 50% in this case, but maintaining similar performance. Lastly, results of limit 32 and 16, performed badly for all datasets, showing the occurrence of loss in representation quality at a linear decay.

7 Conclusions

We proposed two approaches of a representation learning method which intends to provide more effective and compact image representations by optimizing the colour quantization for the image domain. We performed experiments on eight different image datasets comparing the results with a pre-defined quantization approach in terms of performance on the task of CBIR and representations dimensionality.

The first approach, produced representations that outperform the performance of the baseline by a small percentage and presented a two times higher dimensionality. The second approach, which imposes a limitation on the representation dimension, presented results that show improvements on performance for the same dimensionality (128 bins), results that performed better even reducing the dimensionality in 25%, and also others that reduced the representation size until 50% but maintained statistically equivalent performance. Finally, the later approach also had results that imposed a reduction of more than 75% but presented poor performance showing the existence of a lower-bound for lossless compactness and that representations quality declines linearly with the limit.

At the end, the results prove the hypothesis, for the tested scenarios, that it was possible to produce more effective and compact fitness by exploring a colour quantization optimized for the image domain. Moreover, we remain at the end with a method capable of improve already existent feature extraction methods by providing descriptions more effective in terms of representation quality and more compact according to a parametric upper bound.
As future work we plan experimenting on approaches that use fitness functions that consider both effectiveness and compactness in the optimization process as the way of softening the dimensionality increasing. Furthermore, we aim to analyse how the presented approaches behave using different feature extractors and performing over other pattern recognition tasks. As long as the hypothesis were confirmed in these different scenarios, we consider scaling a similar optimization processes for use in GPUs aiming an alternative for Deep Learning approaches.

Acknowledgements This work was financed by CNPq (grant 449638/2014-6), CAPES, and Fapemig (APQ-00768-14). We also thank Microsoft Azure for the Research Grant.

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Fig. 15: Comparison between the Precision-Recall Curves of NLA and BIC feature extractor
Fig. 16: Comparison between the Precision-Recall curves of NLA and BIC feature extractor.
Fig. 17: Comparison between the Precision-Recall curves of LA and BIC feature extractor considering all representation size limits for the datasets Brazilian Coffee Scenes, Coil-100, Corel-1566 and Corel-3906.
Fig. 18: Comparison between the Precision-Recall curves of LA and BIC feature extractor considering all representation size limits for the datasets ETH-80, Tropical Fruits and Vegetables, MSRCORID and UCMerced Landuse
Fig. 19: Comparison between the Precision-Recall curves of LA and GCH feature extractor considering all representation size limits for the datasets Brazilian Coffee Scenes, Coil-100, Corel-1566 and Corel-3906
| Feature Extractor | ETH-80 (AUC) | T. Fruits and V. (AUC) | MSRCORID (AUC) | UCMerced L. (AUC) |
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Fig. 20: Comparison between the Precision-Recall curves of LA and GCH feature extractor considering all representation size limits for the datasets ETH-80, Tropical Fruits and Vegetables, MSRCORID and UCMerced Landuse.
Fig. 21: Comparison between the P@10 results of LA and BIC feature extractor
Fig. 22: Comparison between the P@10 results of LA and GCH feature extractor
Fig. 23: Comparison between the MAP results of LA and BIC feature extractor
Fig. 24: Comparison between the MAP results of LA and GCH feature extractor
Fig. 25: Comparison between the representation size results of LA and BIC feature extractor
Fig. 26: Comparison between the representation size results of LA and GCH feature extractor