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IMAGE SEGMENTATION BY EVOLUTIONARY SPARSE CODES

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ABSTRACT

Find an image for a user of the images are very large, it is a challenging task. Recent research shows that the semantic gap between content-based image retrieval and image means humans. The best way to bridge this gap is automatic semantic annotation. A sparse coding method as a successful method to select features to eliminate noise in the image is used. The main idea of this paper is to provide a method for optimizing Heshin with Nesterov algorithm is coded sparse. Nesterov algorithm to speed up the encoding scheme sparse, convergence rate and the slope predicted for infinite convex optimization convex optimization is applied is limited. To sharpen the image that is used to separate the objects in the image, Laplace settings have been made. In order to optimize the growth of values proposed in this paper, an evolutionary genetic algorithm is used to reach the optimum values over generations could provide good results.

KEYWORDS: Image Segmentation, Sparse Coding, Genetic Algorithm

INTRODUCTION

Image retrieval is comprised of three main methods are manual and traditional image Segmentation and retrieval as text retrieval. Content-based image retrieval using low-level content features such as color, shape and texture will be restored. Automatic image Segmentation and retrieval of texts. The main idea of automatic image annotation, automatic learning of new conceptual models for labeling images [1]. A similar picture can be seen when the semantic labels of text retrieval, the retrieval. Neural coding, how information is represented by a network of neurons in the brain and senses slowly. Sparse encoding natural images best results of the wavelet filters [4].Similar action in the field of cell recipients are vision unit. Sparse coding principles, a set of basic components Dictionary, vector Sparse is alpha. It is clear that there can be an infinite coefficient α can produce a good output. In this paper Heshin and Nesterov for the best value for α are used.

In the field of artificial intelligence, a genetic algorithm is a search heuristic that mimics the process of natural selection. This heuristic (also sometimes called a Meta heuristic) is routinely used to generate useful solutions to optimization and search problems 1. Genetic algorithms belong to the larger class of evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

THE FEATURE EXTRACTION AND IMAGE DISPLAY

The classification and retrieval of images, the images are displayed using low-level features. Since a non-structured array of image pixels, the first step in understanding the meaning of the effective visual features extracted from the image pixels. Both nationally and on the basis of the image cannot display the image, but tends to segmenting the region. Image segmentation consists of segmenting different perspectives such as: region growing. Features Color: Color spaces after the color characteristics of different parts of the image are extracted. Features include: color histogram and color momentum [2] [3]. Texture features include a feature pixel color, but texture features for a group of pixels. The texture feature extraction techniques: texture feature extraction methods, including spatial and spectral methods for texture feature extraction.

SPARSE CODING

Operations and look for ways to reduce errors and increase the quality of the image is used, called image processing. The scope of work with very large images, but generally range considered in four areas of quality improvement, restoration of disturbed images, image compression and image understanding is concentrated by car. Data vectors as a linear combination of a small number of components of a dictionary states. Sparse coding method which is able to select the feature with the lower estimate of the signal acts. Unlike PCA need the orthogonal components of the basic unit of data compatibility. Sparse coding of natural images similar results (even better) of the wavelet filters. Sparse coding applications include removing noise from images, edge detection, precision of thought and compression. In working with large image matrices we deal with it. In this project a different image processing techniques are introduced.

TECHNIQUES FOR AUTOMATIC IMAGE SEGMENTATION

When images are displayed using low-level features, higher levels of meaning can be extracted from image samples. Previous methods for learning the meaning of the image of the user feedback that was being used. In view of the low-level features are extracted from the image content, and these features are classified to a yes or no answer is received. Sorting out meaningful concepts that are used to annotate [5] [6].Laplace setting appropriate boundaries such as gradient to detect because in addition to high sensitivity to noise and disturbances fortification, the two edges of the image processing is causing the error.

SEGMENTATION BY CLASSIFIERS

SVM: For each concept, a classification is required, in which case the set of images that have the concept of positive and negative pictures. During the experiment, each category is a possible decision. Class with the highest probability as the image is being tested. First, image segmentation is the number SVM (the number of concepts) is used. Quality classification of concepts increases, decreases. Decision to be stronger than some of SVM classifier is used to set a number. Each using a separate subset of the training data, it is taught [7] [8].

Bayesian methods: Unlike the binary classification approach in the previous section, a label of an image with a concept or category label attack. View multi-label concept Multi Instance Multi Learning to talk about. In MIML an image by a bag (bag) from the display. Given a set of images to consider that the terms are set, the initial probability models, Bayesian posterior probabilities and conditional trying to get [9]. I suppose an image feature vector X is displayed. We have the same basic probability and conditional probability density. Probability of new image I belong to a particular class is obtained by the following equation:

A Bayesian framework has four main components. Since the distribution function is the same for all classes and class image I can be obtained as follows [10]: Annotations important part Bayesian conditional probability model because the probabilities by counting the number of samples belonging to class achieved.

DATA COLLECTION

- Training and validation data set size = 450 MB
- Test data set size = 430 MB

PASCAL VOC'07 dataset:

Person: per

- *Animal:* bird, cat, cow, dog, horse, sheep
- *Vehicle:* aeroplane, bicycle, boat, bus, car, motorbike, train
- *Indoor:* bottle, chair, dining table, potted plant, sofa, tv/monitor

Table 1

Class	Feature
Aeroplane	Includes gliders but not hang gliders
Bicycle	Includes tricycles, unicycles
Boat	Ships, rowing boats, pedaloes but not jet skis
Bottle	Plastic, glass or feeding bottles
Bus	Includes minibus
Car	Includes cars, vans, people carriers etc.Do not label where only the vehicle interior is shown.
Cat	Domestic cats (not lions etc.)
Chair	Includes armchairs, but not stools or benches
Dining	Excludes coffee table or picnic bench
Dog	Domestic dogs (not wolves etc.)
Horse	Includes ponies, donkeys, mules etc.
Motorbike	Includes mopeds, scooters, sidecars
Potted plant	Indoor plants or outdoor plants clearly in a pot. Excludes flowers in vases
Sofa	Excludes sofas made up as sofabeds
Train	Includes train carriages, excludes trams
TV/monitor	Standalone screens (not laptops), not advertising displays

ALGORITHMS

- Learn weights Sparse code
- fix the amount of data
- Coefficient Alpha graph
- Updates to converge to the values of the above parameters (weight, culture and the factor graph) [11]

ALGORITHM

Objective: To learn the codes Sparse weights.

The algorithm is optimized for the following relationship.

$$\min_{D,W,\alpha} \frac{1}{2l}\sum_{v=1}^{V+1}\|X_L^{(v)} - D^{(v)}W_L\|_F^2 + \frac{1}{2(N-l)}\sum_{v=1}^{V}\|X_U^{(v)} - D^{(v)}W_U\|_F^2$$
$$+\gamma_1\|W\|_{1,\infty} + \gamma_2\sum_{v=1}^{V+1}\|(D^{(v)})^T\|_{1,\infty}$$
$$+\gamma_3 tr\left(W\left(\sum_{v=1}^{V+1}(\alpha_v H_v)\right)W^T\right)$$
$$\text{s.t. } \|D_i^{(v)}\|^2 \leqslant 1, \quad 1 \leqslant i \leqslant N_d, \ \sum_{v=1}^{V+1}\alpha_v = 1, \ \alpha_v \geqslant 0,$$
$$W = \{W_L, W_U\}$$

$\{x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(V)}, y_i\}$: Set of input data and output labels in the view V.

$\{D^{(1)}, D^{(2)}, \ldots, D^{(V)}\}$: Dictionary data in different views.

$\varphi(W)$: Regulator to control Sparse code.

ALGORITHM

The goal

- Learn weights Sparse code optimization using Nesterov:
- A method for increasing the speed of the method.
- reduction method for infinite convex optimization for large problems.
- projected gradient method for convex constrained optimization. [12]
- A method for accelerating convergence.

$$\min_W \frac{1}{2l}\sum_{v=1}^{V+1}\|X_L^{(v)} - D^{(v)}W_L\|_F^2 + \frac{1}{2(N-l)}\sum_{v=1}^{V}\|X_U^{(v)} - D^{(v)}W_U\|_F^2$$
$$+\gamma_1\|W\|_{1,\infty} + \gamma_3 tr(W\boldsymbol{H}W^T),$$
$$\text{where } \boldsymbol{H} = \textstyle\sum_{v=1}^{V+1}(\alpha_v H_v), \ \sum_{v=1}^{V+1}\alpha_v = 1, \ \alpha_v \geqslant 0.$$

ALGORITHM

Update the data dictionary.

$$\min_D \frac{1}{2l}\sum_{v=1}^{V+1}\|X_L^{(v)} - D^{(v)}W_L\|_F^2 + \frac{1}{2(N-l)}\sum_{v=1}^{V}\|X_U^{(v)} - D^{(v)}W_U\|_F^2$$
$$+\gamma_2\sum_{v=1}^{V+1}\|(D^{(v)})^T\|_{1,\infty},$$
$$\text{s.t. } \|D_i^{(v)}\|^2 \leqslant 1, \quad 1 \leqslant i \leqslant N_d$$

Alpha Value is Calculated for All Vectors

The following equation to calculate the alpha value of the derivative of the Lagrange function is used.

$$\alpha_v = \frac{(1/tr(WH_vW^T))^{1/(r-1)}}{\sum_{v=1}^{V+1}(1/tr(WH_vW^T))^{1/(r-1)}}.$$

GENETIC ALGORITHMS

Genetic algorithm to simultaneously consider multiple points of the search space and thus increases the chances that converge to a local maximum, decreases. Search in more conventional ways, the decision rule governing this case serves to move from one point to another in a matter of searching this way can have a maximum bite. Because they may converge to a local maximum. But the whole population of the genetic algorithm (strings) to produce and test each point individually by combining quality (content) of spots, a new population, which includes the improvement of has the form. Apart from doing a search, consider the same number of points in the genetic algorithm, which makes it adaptable to parallel machines because of the evolution of each point, is an independent process. The genetic algorithm only requires information on the quality of the solutions produced by each set of variables. If some optimization methods require derivative information or even need to have a complete understanding of the structure of matter and variables. Because genetic Algorithm not require such specific information on the issue is thus more flexible than most search methods. The genetic algorithm is a search method, which is to guide the search for methods of use random selection will vary 6**Error! Reference source not found.**. Although the decision as to define methods of accident and chance, but the search space is not a random walk. Genetic algorithms are suitable for the crash exploit a priori knowledge they use to solve the nearly optimal to quickly reach it.

The coding problem and a fitness function to determine the barrier population over generations by using the operators of selection, mutation and cutting, elitism is to involve the local optimal solutions. Elitism in the replacement of a case is done. The coding of chromosomes and the problem:

1	0	0	1	1	.....	0	0	1	1	0	0	1

Figure 1: Coding Problem in Genetic Algorithms

FITNESS FUNCTION

Fitness Changes in the genetic algorithm as the fitness function, the objective function is considered. Linespace function in Matlab software the specified range is divided into 100 so that the fitness value is used calculation.

This function has a minimum and maximum value and the boundary value of the chromosome is randomly generated value between these two values to be given. Limit values based on data obtained from the data collection phase of the two intersections Flowers and knowledge of governmental requirements.

Fitness = 1 / α_v

SELECTION OPERATOR

The selection of parents in genetic algorithms to further its chances of reproduction of the members that have higher fitness. There are several ways to do this. A technique that is commonly used selection method using a wheel 8**Error! Reference source not found.**. The implementation of this method is as follows: A - the fitness of all members of the population and thus the suitability of the call stack. (B) a randomly generated number n, so that it is a number between zero and total fitness. (C) The first member of the population that add elegance to the fitness of the population of the former is larger than or equal to n restore. Effects of parental choice back wheel of a parent is randomly selected. Although the selection process is random, the chance that each parent is selected is directly proportional to its fitness. The balance in the number of generations the genetic algorithm with the lowest fitness of the disposal and the release of genetic material in the most graceful members of help. It may be the worst member of the population can be chosen by the algorithm (because anyway there is a random element in the algorithm.) In the population acts of violence, however, are negligible and the assumption that members of a generation, the next generation is much more likely to desorption. However, after many generations, the members of the population are excreted. Parents should be careful in the process of selecting a range of fitness levels should be positive integers.

CROSSOVER OPERATOR

The performance of this operator and mutation operator causes the fibers produced during reproduction, the parents are different disciplines. In nature, this function occurs when two parents exchange portions of their corresponding fields and genetic algorithms, operator communication, exchange of genetic material between the parent sequences to the child (discipline) create there **Error! Reference source not found.Error! Reference source not found.**. There are several types of exchange operator. But the most famous exchange operator used in genetic algorithm is a function of a point**Error! Reference source not found.**. The genetic algorithm is the operator in the manner described below may apply.

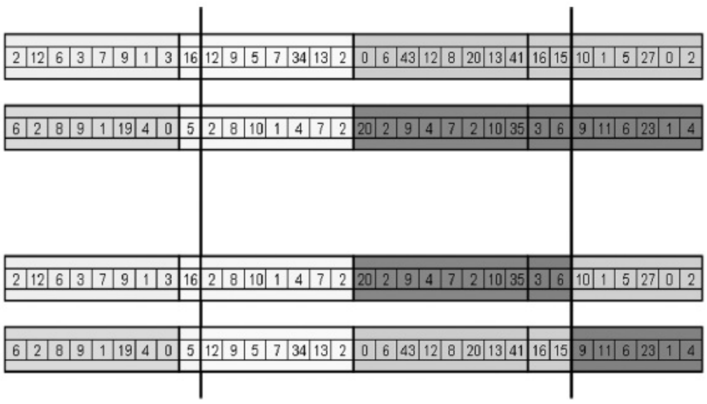

Figure 2 : A View of the Intersection Operator

To be able to use this function need to have two fields. The selection operator is applied to the current population of the two strands of the double-take then do a test to determine the probability that the exchange operator acts on two fields it or not. This test is done using a heterogeneous coin, this means that the probability (P crossover) milk and with probability of crossover line comes from9. For example, if the applied field with a tap on the coin exchange operator, we assume that we have thrown a coin into the milk. Then enter the next phase of the implementation of the exchange operator, we generate a random number between one and the length of the string. After determining the location of the integer that represents the exchange of strings two strands of the location of this specifies the number of broken and distal parts are interchangeable with each other. All parts are separated from each other are connected to the new string is obtained.

MUTATION OPERATOR

The operator is also one of the operators of genetic algorithms and the ability to use genetic algorithms to find near-optimal solutions increases. Mutations, random changes in the value field is a special situation. By applying this operator characteristic that is absent in the parent population, is created. Because mutations alter a gene, i.e. if the value is zero, and vice versa if it is a zero. So why the change is characterized by a series of premature convergence and to not be perfect. Because one of the causes of premature convergence of the population is members of the same mutation causes the same probability of being members of the new population is much reduced. The implementation of this function is described below.

Figure 3: Mutation Operator

This operator, unlike the exchange operator to compare two strings needed to cover a range of needs, after the exchange operator acts on two fields and two new strings to the operator of mutations to the double-stranded is applied to either separately. The method is applied to the individual elements of a string, mutation testing is done. If this test is successful, the status is changed from one to zero or from zero to one, and the so-called mutations. Test the possibility of using heterogeneous coin with probability (P crossover) milk and with probability line comes with a coin toss will be done and if the milk is collected bit value of the mutation 10. As noted above, the probability for each state of a field test should be performed. In other words, for every mutation released once the coin is heterogeneous with regard to the outcome, finds little bit mutation or a mutation goes no further.

ELITISM

With regard to a possible value can be a percentage of the population without mutation and crossover operators are transferred to the next generation. This amount is likely to vary depending on the values that make up the result set. Genetic algorithm performance is significantly dependent on the different stages of the skins. For instance, each of the following: improve the efficiency of the routing issues.

SIMULATION

- Code for feature extraction and preprocessing data files Matlab software has been implemented in a number m.
- The parameters used in the code are:
- {x1, x2,. . . , Xn, Yi} vector image feature values and output labels.
- Pv my next feature vector v.
- W to optimize the weight vector of Hessian.
- γ. weighted index of the parameter C is shown in programming.
- H vector regulator Hessian formula.
- D data dictionary. Display input data from different views.
- Set the Laplace method for separating objects in the image to sharpen the image is used.
- SVM support vector machine: 2 classes can be generalized to multi-class classifier performance with a variety of bands category.
- Inference as a Bayesian statistical approach to the problem is that if all the parameters of the problem is the best approach.
- The results are compared between the different features that include:

GIST	RGB V3H1	RGB	Lab V3H1	Lab	HSV V3H1	HSV	Dense Hue
Harris SIFT V3H1	Harris SIFT	Harris Hue V3H1	Harris Hue	Dense SIFT V3H1	Dense SIFT	Dense Hue V3H1	

The output of each algorithm as follows:

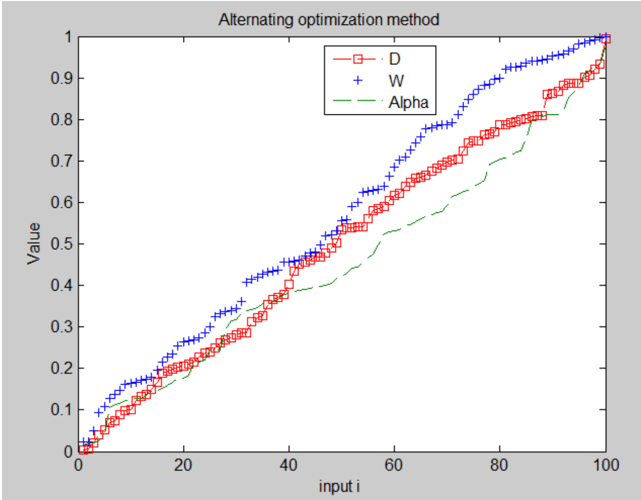

Figure4 : Output Alternating Optimization Algorithm for the Parameters D, W and α

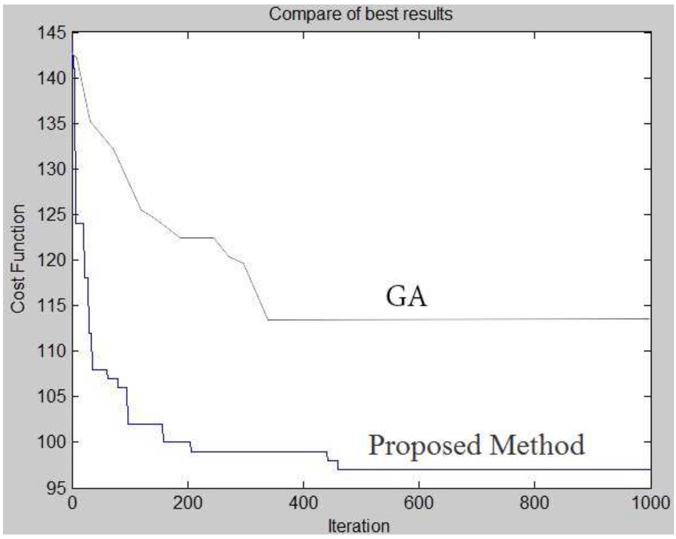

Figure 5: Optimized Parameters D, W and α with GA

Note that the formula used for parameters D, W and α are close to the optimal value, so the graphs represent the values are optimized and enhanced performance.

CONCLUSIONS

Sparse coding approach is successful in the selection of features. That show a feature vector as a linear combination of a small number of components of a dictionary is already defined. Dictionary and Sparse coding coefficients in the formula can be found separately. Sparse coding is based on Laplace setting. Laplace method bias towards fixed functions and it reduces the power of generalization. Sparse coding can be used as the main method in many image processing applications has become. Sparse alpha coefficient coding is important in optimizing the weights.

Using genetic algorithms, we design a function or a function of several variables. Then we have provided data for some variables. The genetic algorithm will execute the functions and variables that are searched. Simulations show that the genetic algorithm is better than the results of the algorithm is the mass of the particle mass. Complete evaluation shows the basic parameters defined by the operator of the genetic algorithm and the results are very impressive.

Due to the quality parameters of the algorithm and the results of simulation in the last section, we discuss evaluation parameters of the latent image. Simulation results of the project based on the ratio of the mean square error is obtained better results than other articles. One of the drawbacks of evolutionary algorithms are a long time to reach the best response. To solve this problem, we can answer or end points to reach to a certain extent be considered Optimality and evolutionary algorithm techniques used immediately. Since the introduction of soft computing methods and techniques rather mixed results are better. Smart ways to optimize it can be used again. The parameters presented in this project can be a good basis for further research in the area of the latent image.

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