Silhouette Coefficient Based Approach on Cell-Phone Classification for Unknown Source Images

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Abstract—Cell-phones have become a necessary communication accessory in daily life. MMS (Multimedia Messaging Service) used by smart phones has caused higher requirement on mobile image manipulation. Classifying image source cell-phones has become a major issue in the cell-phone communication forensics. There are two ways usually used for tracing and identifying the source device: image characteristics and equipment fingerprint. Both of the above schemes require a set of images captured by known source cell-phones for training a classification model. To avoid using any prior knowledge in practical scenarios, a graph based approach was proposed to classify the source cell-phones. Though an acceptable result has been obtained, a problem of incomplete classification appears in the case that one image is classified wrong into a single subset. In this paper, a silhouette coefficient based algorithm is proposed for source cell-phone classification. The spectral clustering algorithm is adopted in graph partitioning and the silhouette coefficient is used to extract the optimal classification from all the possibilities of classification. Experimental results show the validity of the proposed method.

Keywords-source classification; cell-phone image; silhouette coefficient; pattern noise; graph partitioning

I. INTRODUCTION

These years, the capability of cell-phone is developing quickly and it has become a new media to transfer info and come into every aspect of our society. With cell-phone's function increasing, it has played an important role in multimedia communication. Images taken by cell-phones can be used in many aspects of multimedia communication. The authenticity and the source of cell-phone images have attracted more and more attention. Therefore, forensics in the communication systems has become a new hot issue.

To classify mobile images and verify the source cell-phone, the method based on image multi-dimensional statistical features [2] is commonly used. The algorithm in [2] using static features extracted from images is based on supervised learning. The method requires a set of known source images to extract the characteristics of each cell-phone and uses the multi-dimensional statistical features to train a multi-class classifier. Then the given images can be classified using the trained model. Another kind of method such as [3] is based on the principle that each cell-phone's sensor pattern noise is unique. They believe that the sensor pattern can be used as the fingerprint or "bullet scratch" of digital cell-phone [4]. The approach used to attain a cell-phone's sensor pattern noise is to average the noise residuals of a number of images from the same cell-phone. Above two common methods both require a number of known source images as the prior knowledge. However, in many practical application scenarios such requirement cannot be satisfied, there may be nothing known about the given image set. Can we classify the given images based on the different source cell-phones without any prior knowledge? To achieve this aim, Liu proposed a graph based approach [5] in 2010. This graph based approach transforms the source cell-phone identification problem into a source cell-phone classification problem based on graph partition through establishing a weighted graph. In this way, no extra auxiliary images nor any prior knowledge about the constitution of the image set are needed. However, the algorithm has a limitation that there must be at least two images taken by the same cell-phone, because it is the converging condition of the algorithm. Under this loop condition, it reduces to the incomplete classification result.

To solve this problem, a novel cell-phone image classification approach based on silhouette coefficient is proposed. The central idea of the approach is to attain all the possibilities of classification and extract the optimal one by the silhouette coefficient. It cancels the limitation and the loop condition of the approach in [5]. The improved method performs wider applied scope and improves the accuracy of the graph based approach.

The rest of this paper is organized as follows: Section II describes the graph based approach in brief and analyzes the imperfection of the algorithm. In Section III, we propose the silhouette coefficient based approach in detail. Experimental results are presented in Section IV, and finally, we conclude the paper in Section V.

II. THE GRAPH BASED APPROACH

A. Description of the approach

The graph based approach [5] changes the source cell-phones identification into the graph partition issue, which means image clustering. The algorithm can be described in two steps: graph construction and graph partitioning.

We define the given image set as ℓ, there are N images in the ℓ. Each image in the ℓ is defined as $I_i = 1, \ldots N$. The graph based approach considers each image as a node in a weighted graph, we define nodes by $v=\{V_i\}, i=1,\ldots N$. The construction of the graph is based on the relativity between two images. The graph can be represented by the affinity matrix $W=\{\omega_{ij}\}$, ω_{ij} represents the weight of edge in the graph. The weight is defined as:

$$\omega_{ij}=\begin{cases}0, & \text{if } corr(r_i,r_j)<0 \\ corr(r_i,r_j), & \text{otherwise}\end{cases} \tag{1}$$

with

$$corr(r_i,r_j)=\frac{(r_i-\bar{r}_i)\bullet(r_j-\bar{r}_j)}{\|r_i-\bar{r}_i\|\cdot\|r_j-\bar{r}_j\|} \tag{2}$$

r_i represents the noise residual of image I_i, which can be attained by the algorithm in [6].

According to the affinity matrix, we can get the abstract graph. There are N nodes in the graph. Then the question turns to the graph partition. The approach used in the graph partition is the spectral clustering algorithm [7]. Multi-class spectral clustering algorithm according to the affinity matrix $W=\{\omega_{ij}\}$ calculates the matrix eigenvalues and eigenvectors, then attains the optimized partition indicator vectors. The partition result can be denoted by an $N\times L$ indicator matrix $X=[x_1,\ldots x_L]$. L is the number of subsets after graph partition. The partition of N nodes into L subsets υ_j, $j=1,\ldots,L$. Because each node is assigned to one and only one subset, the indicator matrix is belonged to (3) and (4).

$$X_{ij}=\begin{cases}1, & \text{if } V_i\in\upsilon_j \\ 0, & \text{otherwise}\end{cases} \tag{3}$$

$$X\begin{pmatrix}1\\ \vdots \\ 1\end{pmatrix}_L=\begin{pmatrix}1\\ \vdots \\ 1\end{pmatrix}_N \tag{4}$$

Because we have no knowledge about the given image set, the partition number L is unknown. To ensure the value of L, the algorithm creates a condition to stop the partition. It limits that each source cell-phone of the images must contain at least two images. L starts from 1, after every loop L++, then judging the number in the smallest subset. If the number of images in the smallest subset equals to one, the partition stops and (L-1) is the final result. Therefore the end condition of the loop is that the number of images in the smallest subset equals to one after spectral clustering algorithm, because it doesn't agree with the limit condition. The limiting condition is an indispensable part of the graph based approach. But the condition results in unsatisfactory results. In the next part the problem will be shown.

B. The limitation of the approach

To verify the graph based approach, we conduct some different experiments on both indoor and outdoor photos. Most of the experiments can attain the expected results, but during the experiments, we incidentally found there were situations that the classification didn't completely finish. We extend the experiment and analyze the reason of this situation. The algorithm stopped because of the loop condition of the algorithm. For example, we conduct an experiment on a set of photos taken by five cell-phones. The information of cell-phones and photos are listed in Table Ⅰ.

For each image, noise residual is computed on the green channel of the upper left 1280×960 corner.

TABLE I. 5 CELL-PHONES USED IN EXPERIMENT

ID	Cell-Phone Model	Number	Resolution
1	Sumsung i9000	20	2560×1920
2	Sumsung SCH-W899	17	2560×1920
3	Sony Ericsson U20i	20	2592×1944
4	Sony Ericsson E15i	23	2048×1536
5	Motorola Milestone	20	1280×960

There are five cell-phone models in our experiment, however the algorithm misclassifies the images into three categories as Table II shown.

TABLE II. Classification Accuracies Of 5 CELL-PHONES

Subsets	SumS1	SumS2	SE1	SE2	Moto
1	19	0	10	13	3
2	1	10	0	2	15
3	0	7	10	8	2

The partition stops when it finds that the number of the smallest subset equals to 1 with L=4, so the final result is L=3. According to the result of the experiment, we analyze the process of the algorithm. The loop condition of the algorithm is that if the number of the smallest subset after the spectral clustering algorithm is less than two, the classification would be completed. However, if a single image was classified wrong, i.e. the smallest subset with only one image appeared. According to the end condition, the algorithm would stop. That's why the experiment result presents in Table II. According to the analysis, we improve the graph based approach starting from the loop condition. Can we attain the optimal classification without the loop ending condition? Therefore, the silhouette coefficient based approach is proposed.

III. SILHOUETTE COEFFICIENT BASED APPROACH

The main idea of the new proposed approach can be explained in two steps: firstly adopting traversal method attaining all possible classifications with L from 1 to N, secondly extracting the optimal solution using the silhouette coefficient. In this way it can solve the problem existing in the original method.

Given an image set ℓ which contains N images, we cancel the end condition of the graph based approach, which means that the silhouette coefficient based approach is also applicable to the case that there is only a single image from one cell-phone. Because we have no prior knowledge about L, the actual number of subsets L ranges from N to 1. The central idea of the fast image clustering based on spectral graph partitioning algorithm is to conduct spectral clustering algorithm at every loop with L valuing from N to 1 and record the current partition P_L at every loop. Then the right partition number L^* and the corresponding partition P_{L^*} are selected as the optimal clustering. Then the criterion based on the silhouette coefficient [8] is used. The use of silhouette coefficient combines both the measures of cohesion (inside subsets) and separation (among subsets). We use the image's residual noise r_i to calculate the coefficient s_i of each image. The formula of the coefficient s_i is described as (5):

$$s_i = b_i - a_i \tag{5}$$

- a_i (cohesion): the average correlation of r_i to all other noises in the same subset.
- b_i (separation): the average correlation of r_i to all other noises in each of the other subsets, taking the average value with respect to all subsets.

s_i is a correlation measure of the current partition of every image. At the iteration i, a global measure of the silhouette coefficient SC_L is calculated as (6) showed by averaging the coefficients related to each noise that belongs to a certain cluster and taking the average value with respect to all the current L-clusters. We apply this calculation at each loop of the algorithm and achieve all classification possibilities' silhouette coefficient SC_L with L from N to 1.

$$SC_L = \frac{1}{N}\sum_{i=1}^{N} s_i \tag{6}$$

The minimum coefficient over the (N-1) is obtained and the corresponding index L^* is chosen as the optimal source number. Once L^* is ensured, the optimal clustering can be selected by simply extracting the partition P_{L^*}. Here is the pseudo-code of the algorithm adopted:

1) **Step1:** Calculating the affinity matrix $W = \{\omega_{ij}\}$.
2) **Step 2:** Loop over $L \Leftarrow N$ to 1
   a) Graph partition adopting spectral clustering algorithm, and saving the current partition P_L at every loop.
   b) Loop over $i \Leftarrow 1$ to $N-1$, calculate s_i.
   c) Calculate the silhouette coefficient SC_L and save it at every loop.
3) **Step3:** Calculate the minimum value of the silhouette coefficient: $L^* \Leftarrow \min_L(SC_L)$.
4) **Step4:** Get the optimal partition by the iteration L^*, P_{L^*} and that is the partition.

IV. EXPERIMENTS

To verify the performance of the proposed approach, we conduct experiments using 5 cell-phones in Table I. The experiment result using the proposed approach is shown in the Table III.

TABLE III. Classification Accuracies Of 5 CELL-PHONES

Subsets	SumS1	SumS2	SE1	SE2	Moto
1	18	0	2	0	0
2	0	16	0	1	0
3	0	1	17	0	0
4	0	0	0	21	0
5	2	0	1	1	20

The graph based approach is described as A, and the improved approach is described as B. The two experiments' comparison is showed in Table IV.

TABLE IV. Comparison of A and B approaches

Subsets	A					B				
	ID 1	ID 2	ID 3	ID 4	ID 5	ID 1	ID 2	ID 3	ID 4	ID 5
1	19	0	10	13	3	18	0	2	0	0
2	1	10	0	2	15	0	16	0	1	0
3	0	7	10	8	2	0	1	17	0	0
4						0	0	0	21	0
5						2	0	1	1	20
Ave. Accuracy	95 %	59 %	50 %	0 %	0 %	90 %	94 %	85 %	91 %	100 %

To verify the accuracy of the proposed method, we use both indoor and outdoor photos taken by 8 cell-phones. The information of cell-phones and photos are showed in Table V. For each image, noise residual is computed on the green channel of the upper left 640×480 corner.

TABLE V. 8 CELL-PHONES USED IN EXPERIMENT

ID	Cell-Phone Model	Number	Resolution
1	Sumsung i9000	20	2560×1920
2	Sumsung SCH-W899	17	2560×1920
3	Sony Ericsson U20i	20	2592×1944
4	Sony Ericsson E15i	23	2048×1536
5	Motorola Milestone	20	1280×960
6	Nokia 7610	20	640×480

7	Nokia N73	22	640×480
8	Nokia E50	23	640×480

The experiment result shows in the Table VI.

TABLE VI. Classification Accuracies Of 8 CELL-PHONES

Subsets	ID 1	ID 2	ID 3	ID 4	ID 5	ID 6	ID 7	ID 8
1	18	0	2	0	0	0	0	0
2	0	16	0	0	0	0	0	0
3	0	1	17	0	0	1	2	1
4	0	0	0	21	0	0	0	0
5	0	0	0	1	20	0	3	0
6	0	0	0	0	0	18	0	1
7	0	0	0	1	0	0	17	0
8	2	0	1	0	0	1	0	21
Ave. Accuracy	90%	94%	85%	91%	100%	90%	77%	91%

The experiment results show that the silhouette coefficient based approach can have a better performance than the graph based approach. The improved approach can have a better clustering result which is closer to the number of cell-phone models.

V. CONCLUSIONS

Starting from the previous work [5] and analyzing the graph based approach, we propose a silhouette coefficient based approach. The approach has solved the imperfection of approach in [5]. The improved approach can blindly classify a set of given images without any prior knowledge, and it doesn't impose any restrictions on the set of images. Comparing with the intrinsic approach, the improved approach can be applied to more situations and cannot turn up the case that the classification is incomplete. However, because of the improved approach saving all N kinds of possible partitioning and extracting the optimal one, it must take more memory space and increase the computational complexity.

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