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Gang and Moniker Identification by Graffiti Matching

Wei Tong
Michigan State University
East Lansing, MI 48824
tongwei@cse.msu.edu

Jung-Eun Lee
Michigan State University
East Lansing, MI 48824
leejun11@cse.msu.edu

Rong Jin
Michigan State University
East Lansing, MI 48824
rongjin@cse.msu.edu

Anil Jain
Michigan State University
East Lansing, MI 48824
jain@cse.msu.edu

ABSTRACT

Identifying criminal gangs and monikers is one of the most important tasks for graffiti analysis in low enforcement. In current practice, this is typically performed manually by the law enforcement officers, which is not only time-consuming but also results in limited identification performance. In this paper, we present a system that is able to automatically identify the gang or the moniker for a given graffiti image. The key idea of our system is as follows: given a graffiti query, first find a candidate list of the most similar images from a large graffiti database based on visual and content similarity, and then return the most frequent gang/moniker names associated with the candidate list as the tag for the query graffiti. Our experiments with a large database of graffiti images collected by the Orange County Sheriff's Department in California show that our system is (i) effective in determining the gang/moniker of graffiti, and (ii) scalable to large image databases of graffiti.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Retrieval models, Search process

General Terms

Performance, Design, Experimentation

Keywords

Graffiti, Gangs, Moniker, Forensic Databases, Image Retrieval

1. INTRODUCTION

Graffiti are any type of public markings that may appear in forms ranging from simple written words to elaborate wall paintings. It has existed since ancient times, with examples dating back to Ancient Greek and the Roman Empire [1]. Graffiti are a common site in most of the metropolitan regions in the United States and, increasingly, they have been viewed as a growing problem for cities in many other countries. Graffiti have been said to provide a unique insight into society, because messages conveyed through graffiti are often made without the social constraint that might otherwise limit free expression of political or controversial thoughts. In that sense, graffiti have been examined and interpreted to understand many social and cultural issues, such as adolescent personality, ancient cultures, and gang activities [2]. Figure 1 shows some examples of graffiti found in different countries. Graffiti are not only an eyesore, but they are also not tolerated in most communities because of its perceived connotations. According to the *Broken Window Theory* [3], "If a broken window is left unfixed, it can quickly encourage more crime and vandalism to the neighborhood because it sends a message of indifference to observers. Graffiti is one element of the broken window theory. Once graffiti show up somewhere, if left untreated, generally more graffiti follow [4]." Many communities have responded by creating a special task force to combat and remove graffiti. As an example, the city of Riverside, California spends more that $1 million each year for graffiti abatement [4]. From the perspective of law enforcement, graffiti are crimes and the monikers (persons who draw the graffiti) are breaking the law. A vast majority of incidence of graffiti vandalism is the result of "tagging", which is committed by juveniles with the primary objective of gaining peer recognition. Law enforcement agencies collect such graffiti and track their authors, i.e. monikers, based on the similarity among graffiti. Figure 2 shows examples of graffiti images drawn by the same moniker. Law enforcement officials around the country have started to prosecute monikers with harsher sentences than ever, pushing for felony charges, real prison time and restitution payments as they seek to wipe graffiti from their communities [5].

USA France South Africa

Australia China

Figure 1. Examples of graffiti found in different countries.

Graffiti also play an important role in gang culture. A gang is an organized group of individuals who collaborate for anti-social reasons. Like other organizations, a gang has a social structure that categorizes all of its members and uses recruitment techniques to bring new members into the group. Additionally, gangs provide members and their families with protection from rival gangs as well as any other perceived threats. This collective brotherhood is the main reason why people join a gang, and, as a group, they often rob, sell illicit drugs, steal cars and brutalize individuals. Representing its membership and setting up an effective means of communication among the members are essential for the success and growth of a gang. Gangs use specific clothing, brands, symbols, tattoos, hand signals and graffiti [6] to identify their group and exchange messages. Among these symbolisms, graffiti convey rich information about a gang (see

Figure 2. Examples of graffiti drawn by the same moniker.

Figure 3. Graffiti of the Six Deuce East Coast Crips. The Crips, primarily, but not exclusively, an African American gang founded in Los Angeles in 1971, is one of the largest and most violent street gangs in the United States, with an estimated membership of 30,000. Notice the use of the basic lettering style. The spelling of six is done with a "C" to reinforce the Crip identity. The arrow is used among African-American gangs to express their territory [2].

Figure 3). It is the most visible form of gang criminal activity in a community as well as a form of communication and demarcation of gang territory. Indeed, graffiti are regarded as newspapers or bulletin boards for gangs to communicate messages. Hence, recognition and interpretation of graffiti could aid in understanding gang characteristics, behavior, and their growth. Indeed, gang graffiti are also referred to as "tagging", because they are primarily composed of lines and symbols and essentially used for marking a gang's territory (see Figure 3); they warn intruders or trespassers from rival gangs and even police officers that they are not welcome. Gang graffiti also transmit certain messages, symbolize a gang's power and advertise the sale of drugs. Graffiti are often the first indication that gang activity is present in a community. Consequently, this helps law enforcement agents to uncover the extent of a gang's territory by reading its graffiti. An accurate interpretation of gang graffiti can also assist in understanding its criminal intention in advance. For this reason, many law enforcement agencies photograph and catalog gang graffiti patterns for the purpose of identifying gangs.

Based on our interactions with various law enforcement agencies, both at the local and national levels, gang and moniker identification has become more and more demanding for them [7, 8]. However, in the current practice, this is conducted manually by the low enforcement officers, a procedure which is both time-consuming and has limited performance. To address this limitation, we have designed a graffiti matching and retrieval system that can automatically identify both the gang and the moniker for a given query graffiti image. The key idea is to first identify from a database the graffiti images that share a large visual and content similarity with the query. Under the assumption that similar graffiti images are from the same gang and drawn by the same moniker, we are able to identify the gang and moniker for the query image based on the information associated with the matched graffiti images from the database. We have tested our system on a real graffiti database provided to us by the Orange County Sheriff's Department, California. We note that in our previous study [9] the goal was to develop an image based graffiti matching system.

2. GANG/MONIKER IDENTIFICATION

In order to identify gang and moniker for a given query graffiti image, every graffiti image in the database is manually labeled by its associated gang and moniker. Our goal is to identify the gang and moniker for a query graffiti image by utilizing the labeled images in the database. Given the large number of gangs and monikers, as well as the complexity of the graffiti image matching problem, we allow the system to suggest more than one gang and moniker names for a given query. The system evaluation is based on whether the correct gang and moniker appears in the names suggested by the system.

A straightforward approach to address the above problem is to cast the gang/moniker identification into a multi-class classification problem. More specifically, we can treat each gang/moniker as a separate class. By viewing each labeled graffiti image from the database as a training example, we can train a binary classifier for every gang/moniker to decide if a query graffiti image is created by the gang/moniker. The main shortcoming of this approach is that due to the large number of gangs and monikers, the number of labeled graffiti images is usually very small for each gang and moniker, making it difficult to construct a reliable classifier for every gang/moniker. To be more concrete, for the Tracking Automated and Graffiti Reporting System (TAGRS) database that will be introduced in Section 3, there are more than 4,200 gangs and monikers from the Orange County alone, and, on average, only 14 images are available for each gang/moniker.

In this paper, we propose a search based approach for gang/moniker identification [10]. The main assumption behind the search based approach is that two graffiti images are likely to be created by the same gang/moniker if they bear large similarity

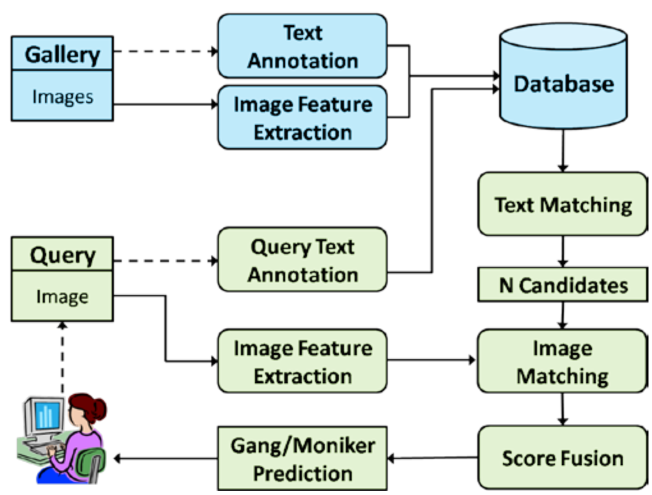


Figure 4. Block diagram of system for gang and moniker identification.

both visually and content wise. We emphasize that it is insufficient to identify the matched graffiti images solely based on the visual content since almost all graffiti are drawn manually in freestyle. As a result, even the graffiti of the same gang or created by the same moniker could vary dramatically in their visual appearance (see Figure 2). We address this challenge by exploiting the textual content of graffiti in the search based approach, where the textual content is based on the letters, numbers and symbols that appear in the graffiti image. The matched graffiti are determined based on a combination of visual and textual similarities. While it may seem attractive to develop a system to automatically recognize the letters, numbers, and symbols from graffiti images using OCR [11], it is not feasible given the current state-of-the-art OCR techniques because of the large variation in the style of graffiti painting.

Figure 4 shows the basic architecture of our system for gang/moniker identification. It is comprised of two components, the offline component (in blue) and the online component (in green). In the offline component, visual features are automatically extracted from the graffiti images in the database, graffiti images are manually annotated based on the occurrence of letters, numbers, and symbols, and this information is stored in the database. In the online component, given a query graffiti image, the system first selects the top *N* candidate images that share large textual similarity with the given query. This filtering step allows us to narrow down the candidates for further matching, and therefore significantly improve the retrieval efficiency. Given the *N* candidate images, an image feature based matching is performed to compute the similarity between the query and every candidate image. The top *k* (*k* < *N*) graffiti with the largest similarity scores are returned as the matched images for the given query. The final identification for the query is made by the *n* most popular gang/moniker names associated with the matched graffiti images.

2.1 Matching Graffiti by Annotation Text

We annotate the textual content of a graffiti image by the presence/absence of 26 letters (a-z) and 10 numbers (0-9). All the capital letters are converted into their corresponding lower cases and all other components in graffiti, such as symbols, are ignored in the current annotation process. If the graffiti image does not contain any recognizable letters and numbers, its annotation is left empty. As a result of the annotation process, the textual content of each graffiti image is represented by a 36-dimensional binary vector.

Let T and T_q be the binary vector representations for a database graffiti image *I* and a query graffiti image I_q, respectively. The textual similarity between *I* and I_q is computed as the Hamming distance between the two binary vectors, i.e.

$$S_T\left(I_q, I\right) = T_q{}^T\, T$$

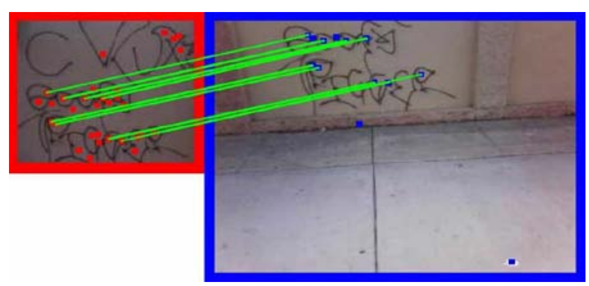
2.2 Matching Graffiti by SIFT Features

We extract Scale Invariant Feature Transform (SIFT) [12] features from graffiti to represent their visual content. SIFT has been found to be highly distinctive in a number of studies on object recognition and image retrieval [9, 13]. A 128-dimensional descriptor representing the texture in a neighborhood around the keypoints in an image is computed. The keypoints are generally invariant to image scaling and rotation, and therefore provide a robust approach for image matching across a wide range of affine distortion, additive noise, and changes in viewpoints and illumination.

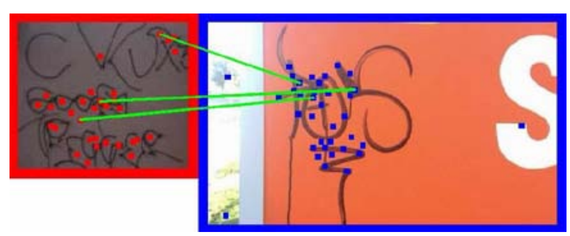
Let $K_i = \{k_{i1}, k_{i2}, \ldots, k_{in}\}$ denote the set of keypoints detected in a database image I_i. To measure the similarity between a query image I_q and a database image I_i, denoted by $S_A(I_q, I_i)$, we compute the number of keypoints from I_q that match with the keypoints from I_i [12]. A keypoint k_q from I_q is considered to be matched to a keypoint from I_i, if the ratio of the shortest (d_1) and the second shortest (d_2) distance from k_q to the keypoints from I_i, is smaller than a predefined threshold γ ($\gamma = 0.49$ in our system). Note that this similarity measure is *asymmetric*, i.e. $S_A(I_q, I) \neq S_A(I, I_q)$. One shortcoming of the asymmetric similarity measure is that it may produce many false matches, particularly if there is a keypoint in the database image I_i whose descriptor is similar to many keypoints in I_q. We address this limitation by defining a symmetric similarity measure: (i) compute the asymmetric match scores between I_q and I and between I and I_q, resulting in two sets of matched keypoint pairs, denoted by $M(I_q|I)$ and $M(I|I_q)$, (ii) compute the symmetric similarity measure, denoted by $S_S(I_q, I)$, as the number of matched keypoint pairs that appear in both sets, i.e.,

$$S_S(I_q, I) = \left| M(I_q|I) \cap M(I|I_q) \right|$$

Compared to the area restriction matching method [13] that was also developed to reduce the number of false matches, one main advantage of the symmetric matching is that the symmetric matching is computationally simple and does not require significant parameter tuning. Figure 5 shows two matching examples, one between a pair of nearly duplicate images and the other between two different images, where the matched keypoints identified by the symmetric algorithm are connected by a green line. Figure 6 illustrates the effectiveness of the symmetric matching by comparing two different images. Note that false matches in asymmetric matching (Figure 6(a)) are removed after applying the symmetric matching (Figure 6(b)).

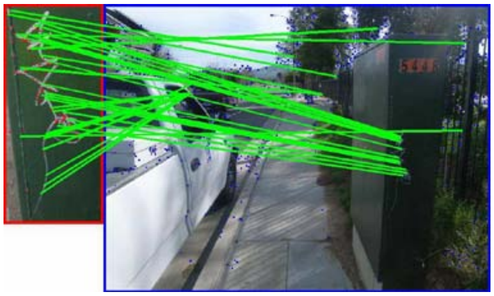


(a) Match score = 10



(b) Match score = 3

Figure 5. Matchings between (a) two similar and (b) two different graffiti images along with the match scores.



(a) Asymmetric matching (match score = 47)

(b) Symmetric matching (match score = 17)

Figure 6. Examples of (a) asymmetric and (b) symmetric matchings with the corresponding match scores.

2.3 Identifying Gang/Moniker

Given the two similarity scores S_T and S_S, the final similarity between I and I_q, denoted by $S(I_q, I)$, is computed as

$$S(I_q, I) = w * S_S + S_T$$

where w is the weight parameter that is determined empirically (see Section 3). Database graffiti images are ranked in a descending order of the similarity score $S(I_q, I)$. We then count the frequency of gang/moniker names associated with the top k most similar images, and return the n ($n <= k$) most frequent gang/moniker names as the prediction for the given query.

3. EXPERIMENTS

We verify the effectiveness of our system for gang/moniker identification on a real-world graffiti image database.

3.1 Graffiti Database

The Tracking Automated and Graffiti Reporting System (TAGRS) database maintained by the Orange County Sheriff's Department [14] is used in our experiments. Figure 7 shows some example images from the TAGRS database. Images in the TAGRS database mainly come from two sources: (i) Orange County Transportation Authority (OCTA) and (ii) the crime reports. For graffiti from both these sources, if available, additional information, such as the moniker, gang or crew names that are associated with the graffiti, and the address, date and time that the graffiti was discovered, is also added to the database. The TAGRS database is comprised of about 64,000 graffiti images that are mostly 640×480 pixels in size. To evaluate the effectiveness of our system for gang/moniker identification, we manually annotated a subset of 9,367 images in this database and selected 185 graffiti as query for testing. For each of these query images, there is a near-duplicate image in the database.

Figure 7. Examples from the TAGRS graffiti database.

3.2 Graffiti Matching Results

We evaluate the retrieval results of our system by using the 185 graffiti images as queries. To establish the ground truth, for every query, we manually find its true matches in the database that are near duplicates. The retrieval accuracy is evaluated by the cumulative matching characteristic (CMC) curve [15], a metric that is commonly used in forensic analysis. For a given rank position M, the CMC score is computed as the percentage of queries for which the correctly matched images are found within the top M retrieved images. Figure 8 shows the CMC curves for the 185 queries, using the textual features (i.e., text retrieval), the visual features (i.e., image retrieval), and a combination of textual and visual features (i.e., text + image retrieval). In the combination setting, the filtering step returns 500 candidate images. The approaches based on the text features and the image features alone yield relatively low performances, with an accuracy of 47.6% for text based matching and 49.1% for image based matching at rank 30. However, a fusion of textual and visual content for image matching improves the overall performance by ~18% (i.e. 65.4% at rank 30) compared to the image based matching.

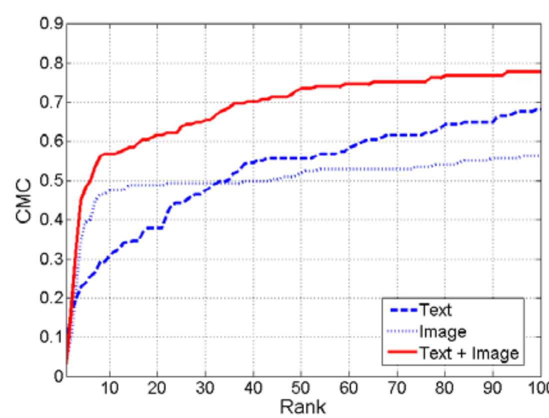


Figure 8. Retrieval performance using different feature representations of graffiti images.

The combination weight w was empirically determined with w = 0.8 providing the best performance. Figure 9 shows an example of the retrieval result. For this example, the true matched image for the query was found at rank 204 in text based matching, at rank 11 in image based matching and at rank 1 in the combination of text and image feature matching.

In addition to the retrieval accuracy, the text features are also used in the filtering step to narrow down the candidate list of matched graffiti. Since it takes significantly less amount of time to perform text retrieval than an image feature based matching, this filtering step results in a dramatic improvement in retrieval efficiency. Table 1 summarizes both the retrieval accuracy and the retrieval time of our system when varying the number of candidate images, *N*, returned by the filtering step. By using only 500 candidate images returned by the filtering step, we are able to reduce the retrieval time by a factor of 20 with slightly better retrieval performance.

Table 1. Performance comparison for different numbers of candidate images (*N*) returned by the filtering step.

No. of candidate images	300	500	1,000	All
Rank-30 Accuracy (%)	63.8	65.4	66.5	64.3
Retrieval Time (s/query)	12.4	20.1	39.8	415.7

3.3 Results for Gang/Moniker Identification

In this experiment, we report the gang/moniker identification results for the 185 test images. There are two parameters in our system for gang/moniker identification: k, the number of matched graffiti images returned by the image matching algorithm, and n, the number of the most common gang/moniker names that are associated with the matched graffiti images.

We first determine the value for k. Figure 10 shows the identification results measured in CMC for different values of k. Similar to the retrieval experiment, for each k, we measure CMC by the percentage of the test images whose gang/moniker is associated with *at least one* of the k graffiti images returned by the matching algorithm. From Figure 10, we observe a very significant improvement in CMC as k is increased from 1 to 10. The improvement becomes less significant for $k > 10$. Based on this observation, we set $k = 10$.

To determine the value for n, note that our system will always predict the n most popular gang/moniker names that are associated with the k retrieved images. To evaluate the effect of n, we use *recall* as the evaluation metric, namely, a prediction is correct if and only if the right gang/moniker is one of the n predicted names. Figure 11 shows the averaged recall for different numbers of predicted names. It is not surprising to observe that the larger the n, the higher the recall. Similar to the procedure for selecting a value for k, we observe a significant improvement in recall when increasing n from 1 to 3. The improvement slows down as n goes beyond 4. As a result, we set $n = 4$. Finally, we report in Table 2 the identification accuracy of the proposed system using $k = 10$ and $n = 4$. Note that in our definition, identification is correct if the correct gang/moniker is among the n returned names. As indicated in Table 2, our system is able to make correct prediction of the gang/moniker names for more than 63% of the queries using a combination of textual and visual features. An example of the identified gang/moniker names by the system is shown in Figure 9 in which the true gang/moniker name is 'sinca'.

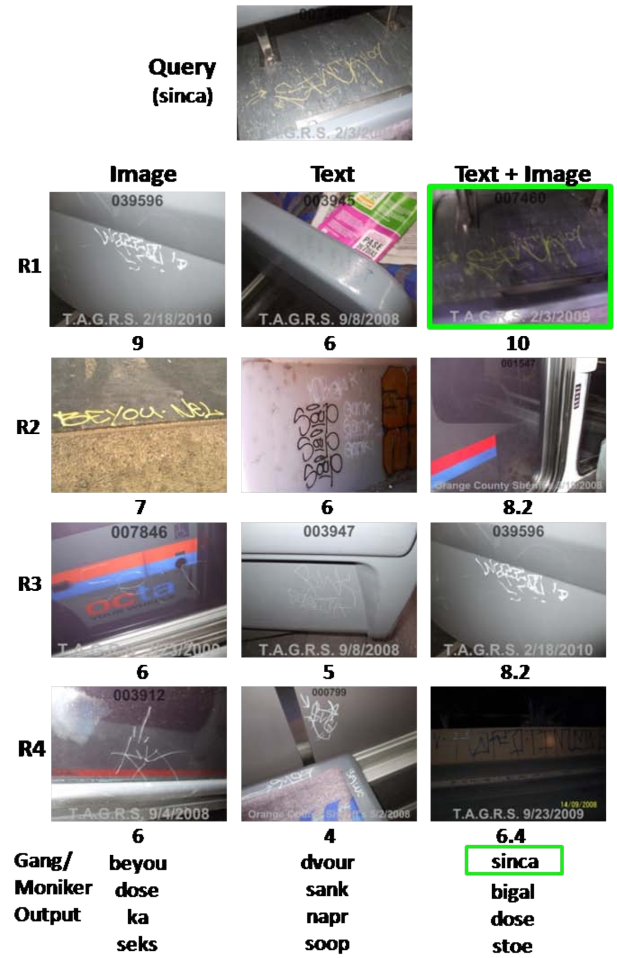


Figure 9. An example of graffiti matching and gang/moniker identification. The number under each image is the matching score. The correctly matched image as well as the identified gang/moniker name is marked in green.

Table 2. Prediction accuracy for gang/moniker identification (k = 10 and n = 4).

Features	Text	Image	Text + Image
Accuracy (%)	31.8	54.1	63.8

4. CONCLUSIONS AND FUTURE WORK

Automatic gang and moniker identification is a very challenging and important problem in law enforcement. We have presented a system to automatically determine the gang/moniker name for a given graffiti image. The system first retrieves images from a database that are most similar to the query in terms of visual and textural contents. The identity of the query is then predicted based on the most frequent gang/moniker names associated with the matched images.

The challenges faced by the proposed system are three folds. First, there are a limited number of graffiti images that are associated with each gang/moniker, making it difficult to directly apply the standard supervised learning techniques. Second, due to the large variance in the visual appearance of the graffiti generated by the

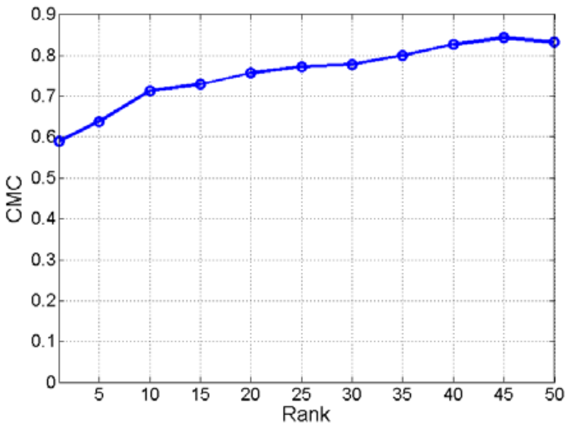


Figure 10. Results for gang/moniker identification using different values of *k*.

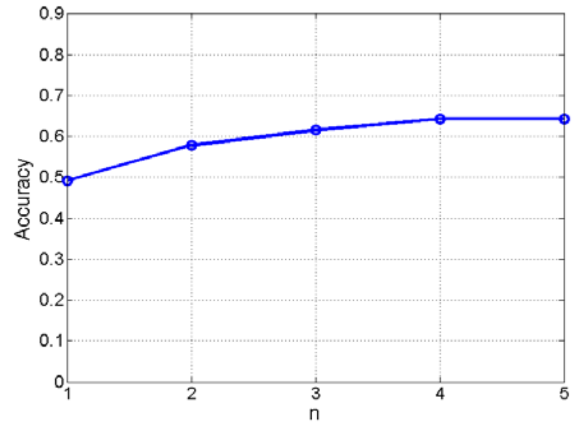


Figure 11. Results for gang/moniker identification for different values of *n*.

same gang and moniker, it is not easy to find the matching graffiti images Finally, due to the large size of graffiti image databases, additional efforts are needed to make the system scalable to hundreds of thousands of images. In this paper, we address the first challenge by developing a search based method for gang/moniker identification. The second challenge is tackled by combining the visual and textual content of graffiti for image matching. By combining the textual and visual content of graffiti, the proposed system is able to improve the overall prediction by 18%. We address the third challenge by introducing a filtering step, based on text retrieval, in the system to quickly remove the irrelevant images. In the future, we plan to explore additional information about graffiti other than the textual features, such as the time stamp and location of graffiti. We also plan to explore visual features other than SIFT for graffiti matching, and to develop more adaptive algorithms to fuse the matching results from different features.

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