OPEN SET FACE RECOGNITION USING ADABOOST AND GEOMETRIC TRANSFORMATION

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Abstract: This paper proposes a new method to address the problem of open set face recognition. Open set face recognition requires the system to recognize identities registered on the gallery (known) set and reject those not registered. Our method, combined the general Adaboost face recognition (GAFR) method with geometric transformation, can overcome the performance bottleneck when closed set recognition algorithms are used for open set task. Experimental results tested on the FERET database have impressively indicated the effectiveness of our method. An example is also provided to show how to expand the general closed set recognition method to the open set task.

1 INTRODUCTION

Open set recognition is significant for the applications of face recognition system. Prior to closed set recognition, open set recognition makes no assumption that all probes (test exemplars) have been registered on the gallery set (known identities database). An open set face recognition system has to decide whether the probes are known identities or imposters. Imposters are rejected, while genuine identities are accepted and then to be classified. Open set recognition is more practical for applications that usually confronts with unknown people.

However, open set recognition is a definitely challenge for modern pattern recognition (Wechsler, 2007). Compared with closed set recognition, open set recognition system has to deal with two more issues of rejecting genuine identities or accepting imposters respectively. It is hard to deal with these two issues at the same time for their contradictory characteristics. This leads to the difficulties in open set recognition task to simultaneously get a high correct classification rate (CCR), the percentage of correctly classified genuine exemplars, and a low false acceptance rate (FAR), the percentage of erroneously accepted imposters. The acceptance-rejection criterion is a threshold, which makes a balance of CCR and FAR to get a reasonable system performance (J. Stallkamp, 2007).

There have been many efforts and algorithms to address the closed set recognition problem (Jones and Viola, 2003; P. Yang and Zhang, 2004; S. Shan and Gao, 2005; Liao and Lei, 2006). Their performance measured by CCR can be above 95 percent. However, they can hardly achieve the same high CCR with low FAR when used in open set recognition system (Li and Wechsler, 2005; J. Stallkamp, 2007; S.Z. Li and Zhang, 2007). Recently, there are also some useful algorithms designed for open set task. Li and Wechsler expanded on the Transduction Confidence Machine to make it suitable for open set multiclass identification (Li and Wechsler, 2005). K-nearest neighbors provided a local estimation of the likelihood ratio. Beside this, their method can set the thresholds ahead of time and obtain similar results when gallery set varies. Their "Open Set TCM-kNN" (k=1) achieved average 88.5 percent CCR with 6 percent FAR in open set recognition task. Stallkamp et al. introduced three weighting schemes to resolve a video-based face recognition problem, including the task of open set recognition (J. Stallkamp, 2007). In their work, KNN was also used to reduce the equal-error rate (EER), a rate value to make balance of three error types in open set recognition task, which leads to a 20 percent EER in their own database.

In this paper, we propose a novel method to address open set face recognition problem. It extends the general Adaboost face recognition (GAFR) method used for closed set task (Jones and Viola, 2003), and makes it suitable for open set task. Because of the trade-off between CCR and FAR, there is a performance bottleneck of open set recognition system. Since threshold plays a role of balancing CCR and FAR, just choosing an optimal threshold is not the best way to make a great improvement to recognition performance.Actually, no matter how to choose the threshold, the performance of recognition algorithm is still influenced by the bottleneck. Taking into account that the errors of genuine exemplars and imposters are mainly caused by the overlap between exemplars similarity distribution, it is an essence way to reduce the overlap area, which will reduce FAR without reducing CCR at the same time and achieve a good recognition result. Inspired by the characteristic of Adaboost method, we combine GAFR method with geometric transformation, and realize an obvious reduction in the similarity overlap. Our geometric transformation Adaboost face recognition (GTAFR) method gets about 10 percent equal-error rate using the well-known FERET database, which is a very competitive result compared to current works.

The outline for the paper is as follows: Section 2 describes open set recognition procedures using boosting method, and provides the utility of geometric transformation. The details of the proposed method are also discussed in this Section. Section 3 describes the use of two speedup strategies, including a two-stage recognition structure and a pre-transformed strategy, which makes the recognition method more efficient. Our approach is evaluated in Section 3, followed by conclusions in Section 4.

2 OPEN SET FACE RECOGNITION

Face recognition methods based on Adaboost is widely used in closed set task. However, it is necessary to make some improvements when the closed set method is used for open set task. The open set recognition method should provide multiclass classification and include a rejection option (Li and Wechsler, 2005).

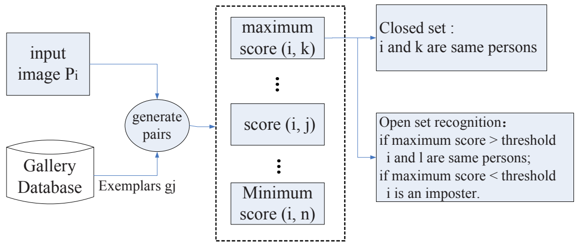

Figure 1: Test procedures of GAFR method used in both closed set and open set tasks.

2.1 Open Set Recognition Method Using Adaboost

The test procedures of GAFR method used in both closed set and open set tasks is shown in Fig. 1. Firstly, a new test image from probe is made pairs with every exemplar in gallery, i.e. (probe, gallery). If the probe and gallery exemplars are same identity, the generate pair is positive, otherwise the pair is negative. Therefore, if the test identity is an imposter, the generated pairs are all negative. The number of all generated pairs is $1 \times n$, where n is the number of exemplars in gallery. Secondly, the generated test pairs are tested by Adaboost cascade classifier which is trained ahead of time. Most of negative pairs should be rejected by Adaboost classifier while seldom positive ones are rejected erroneously. The classifier provides a measure value of credibility and confidence about the passed pairs, which helps the system to make a rejection-acceptance decision. For conventional decision-making methods for closed set, they typically select the pair with the maximum similarity score and classified the probe as same person with the gallery exemplar in this pair. However they can not include a rejection option. Decision-making method for open set, compares the maximum score with a prior setting threshold. If the maximum score is larger than threshold, the corresponding pair is accepted as a positive one. Otherwise, the pair is rejected.

As a criterion to decide whether a test pair is positive or negative, threshold is important for the performance of an open set recognition system. Experiments showed that performance varied greatly with different thresholds in (Li and Wechsler, 2005). Practically, the threshold has to be set up ahead of time using ground truth. An optimally set threshold leads to a best performance of the recognition system. However, the best is limited, for there is a bottleneck in the system performance.

Our method is proposed to break through the bottleneck and achieve a better performance. Fig. 6 shows the similarity distribution of exemplar pairs passed through cascade classifier (un-passed pairs are scored as 0). Most positive pairs distribute in the upper area while most negative pairs are in the lower area. It is obviously that there is an overlap between the two distribution areas. A reasonable threshold is usually chosen in the center of the lower and upper bounds. However, it is impossible to depart all positive and negative similarity scores with a threshold, which is the reason for the performance limitation and the trade-off between FAR and CCR. If the overlap could be reduced, the bottleneck mentioned above would be overcome, resulting in a better recognition performance.

2.2 Geometric Transformation

Geometric transformation means that the image pixels are transformed as a whole in horizontal or vertical direction, rotated on the plain clockwise or anticlockwise, and resized to different scales.

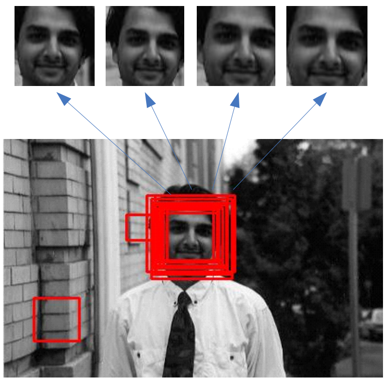

Figure 2: Positive and negative exemplars (areas) which passed the Adaboost classifier in face detection task.

We find that the Adaboost cascade classifier has a stronger tendency to the passed positive exemplars than to the passed negative ones (see Fig. 2). Several candidate exemplars (areas) are detected from numerous positive and negative ones. The detected results contain not only the positive but also a few negative ones. This is the basic use of a positive-negative classifier. Different from this, we find another tendency characteristic from all these passed exemplars: many candidates near face area (the positive exemplar) are detected simultaneously with the detection of the positive exemplar; While no candidate is accepted by the classifier around the no-face area (negative exemplar) which also passed the classifier as the face area. This is what we called tendency characteristic of Adaboost classifier.

Note that the tendency characteristic mentioned here is different from the basic characteristic of positive-negative classifier. The former makes another classification for the pairs which have passed the classifier, while the latter is for all test pairs.

Inspired by the tendency characteristic, we make the same geometric transformation to original exemplars as the relationship between correct face area (the positive exemplar) and its nearby candidates. Eight new exemplars are generated from the original exemplar s, where k is a transformation parameter:

$$T(s,k) = \{s_j | j = 1, \cdots, 8\}. \quad (1)$$

The eight kinds of transformation can be labeled to 3 categories of geometric transformation:

- k-pixel offsets transformation in x axis and y axis;
- On-the-plain rotation with an angle of k, clockwise and anticlockwise;
- Scaling with $(1 \pm k/10)$ factors.

Geometric transformation can be considered as a simple exemplar expanding method, which strengthens the different tendencies of Adaboost classifier to positive and negative exemplars. Although some negative pairs are not rejected but accepted by Adaboost classifier, their expanded exemplars are difficult to pass again. Geometric transformation also can be considered as a disturbance-adding method that gives a few pixel-disturbances to original exemplars. Since the positive exemplar pairs are more robust to these disturbances than negative pairs, geometric transformation method provides another opportunity to depart the erroneously accepted imposters from genuine identities. In a word, combined with geometric transformation, Adaboost face recognition method can reduce the similarity scores of negative pairs and have little impact on the passing of positive pairs, which can decrease the similarity distribution overlap and improve the recognition performance.

2.3 Procedures of GTAFR Method

The Adaboost cascade classifier is composed by several strong classifiers H, while H consists of several weak classifiers h (P. Yang and Zhang, 2004). Equation (2) and Equation (3) show how to compute the similarity score and the output decision of a general Adaboost strong classifier respectively, where x is an exemplar and b is a threshold selected in the training procedures.

$$H\_Conf(x) = \sum_{t=1}^{T} h_t(x), \quad (2)$$

$$H(x)=\begin{cases}1, & \sum_{t=1}^{T} h_t(x) > b \\ 0, & \sum_{t=1}^{T} h_t(x) \le b\end{cases}. \tag{3}$$

For exemplars are expanded in the proposed method, it is necessary to define a new acceptance-rejection criterion. Recognition decision for a test pair should be made by similarity scores computed from its extended pairs:

$$F\_Conf(|p-g_i|) = H(|p-g_i|) \times \frac{\sum_{j=1}^{8} H\_Conf(|p_j - g_i|)}{8}, \tag{4}$$

$$F(|p-g_i|)=\begin{cases}1, & F\_Conf(|p-g_i|) > \varepsilon \\ 0, & F\_Conf(|p-g_i|) \le \varepsilon\end{cases}, \tag{5}$$

Where p is the original probe, p_j is the extending exemplars, g_i is exemplars from the gallery set G to compose a test pair with the probe. Threshold ε depends on the application, i.e. the image quality and the composition of training data. The training procedures are based on the same idea as (S.Z. Li and Zhang, 2007) in a leave-one-out manner.

The steps of testing a probe face image are as follows:

1) Define the probe image is p, the gallery set is $G = \{g_i \mid i = 1,...,n\}$, n is the number of known images in gallery. The transformation parameter k and threshold ε are set manually ahead of time.

2) Make geometric transformation to p and g_i, generate $\{p_j \mid j = 1,...,8\}$, $\{g_{ij} \mid j = 1,...,8; i = 1,...,n\}$. Before the transformation, the original test pairs generated by probe and gallery images are: $\{(p, g_i) \mid i = 1,...,n\}$. After transformation, the test pairs are: $\{(p_j, g_{i1}), (p_j, g_{i2}), ..., (p_j, g_{i8}) \mid j = 1,...,8; i = 1,...,n\}$.

3) Classify positive and negative pairs by Adaboost classifier, obtain the similarity score of each pair using Equation (4).

4) Sort the similarity scores. If the maximum score is larger than ε, p is the same identity with g_i in the maximum-scored pair. Otherwise, p is rejected as an imposter.

3 SPEEDUP STRATEGIES

Because the original exemplar is expanded to eight exemplars, the test time that the new approach needs is eight times longer than the time original method needs. In order to speed up the recognition process, we propose a two-stage recognition structure as well as a pre-transformed strategy for the exemplars.

3.1 two-stage recognition structure

The n-stage searching structure has been used in many works so far (R. Feraund and Collobert, 2001), (T.F. Cootes and Lanitis, 1994). Here we also use its coarse-to-fine scheme to improve the efficiency of our method. Fig. 3 illustrates the two-stage structure. The process begins with testing the unknown image with original exemplars p and g_i. Most of the negative pairs are discriminated from positive pairs in the first stage. The remaining negative and positive pairs are then expanded by geometric transformation and made a fine recognition in the second stage. The classifiers used in stage one and two are the same, there is no need to train it again.

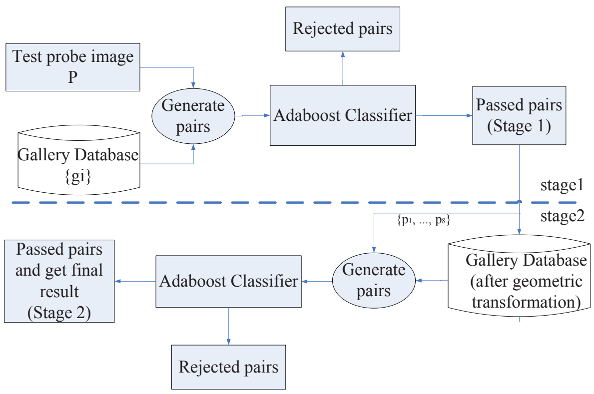

Figure 3: Two-stage recognition structure.

The advantage of two-stage structure is that, most of negative pairs are rejected in the first stage, and only a small percent of all test pairs are passed to the next stage. Hence, the geometric transformation and testing time in second stage are greatly saved.

3.2 pre-transformed strategy

Of all the exemplars from the probe and the gallery set, only the probe image is unknown, while the exemplars in gallery set have been enrolled. Therefore, we can make a pre-transformation to the gallery images ahead of time, and store them in a database (see Fig. 3). When they are needed in the recognition process, system can easily get the transformed data without computing.

4 EXPERIMENTS

Our experiments include two parts: First, the tendency characteristic of Adaboost cascade classifier is tested on FERET database (P.J. Phillips and Rauss, 2000), and give an answer whether geometric transformation can make the first-stage-passed positive exemplars much easier to pass the classifier again than first-stage-passed negative ones. Second, our GTAFR method is evaluated on the challenge FERET database and made performance comparison with GAFR and other works.

4.1 Experiment Design

There are several widely used performance measure methods. Different CCRs have been compared under the assumption of an equal FAR to evaluate their performances (P.J. Phillips and Bone, 2003). However, this method can not indicate the trade-off of errors between positive and negative exemplars. In this paper we use Reciver Operating Characteristic (ROC) curve, which can assess how FAR affects CRR and the functions of the threshold. Another useful measure method is to compare the EER (S.Z. Li and Zhang, 2007), which shows the balanced error rate for both positive and negative exemplars. EER is computed by Equations (6)-(8). Let N be the number of exemplars in probe set, which includes N_p genuine exemplars and N_n imposter exemplars. After recognition, N_{pt} ones are correctly classified and N_{pf} ones are erroneously classified (include false rejections and classified as wrong identities) in genuine exemplars; In imposter exemplars, there are N_{nt} ones correctly rejected and N_{nf} ones erroneously accepted.

$$CCR = \frac{N_{pt}}{N_p}, \tag{6}$$

$$FAR = \frac{N_{nf}}{N_n}, \tag{7}$$

$$EER = 1 - \frac{N_{pt}}{N_p} = \frac{N_{nf}}{N_n}. \tag{8}$$

To avoid image differences in illumination, face position and other disturbance factors, all exemplars should be processed as Fig. 4 before training and testing. Firstly, every exemplar is rotated with eyes positions to get an upright face and every face is resized to 20x20. Then exemplars are normalized (zero-mean and unit variance) to remove the impact caused by different illuminations. Finally make a mask to avoid the disturbance from background and hair.

4.2 Tests on Geometric Transformation

We tested on the FERET set of FA and FB images, which vary only in face expression. The 1196 FA images are used as gallery images and the 1195 FB images are used as probes. All identities (with 1 exception) in gallery have exactly unique mates in probe set.

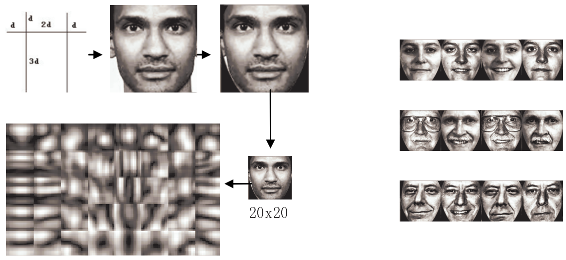

Figure 4: Face image normalization before training and testing.

There is only one positive pair for each probe; the remaining 1195 pairs for each probe are negative. Therefore, the FA/FB set can give an evaluation to the efficiency of geometric transformation, although it is usually used for closed set recognition task.

We choose the passed pairs (positive and negative ones) located in the similarity overlap area to conduct this experiment, because the similarity tendency characteristic of Adaboost is for the passed exemplars, and also because these negative passed pairs can hardly be rejected by usual methods. We make the same geometric transformation to all passed pairs, and test that whether positive and negative ones can be discriminated after transformation using the same classifier.

Table 1: Passed rates before and after geometric transformation.

	Total Number	Passed Number	Rejected Number	Passed Rate
PosBefore	467	467	0	100%
PosAfter	467	446	21	95.5%
NegBefore	1026	1026	0	100%
NegAfter	1026	87	939	8.5%

A comparison between the passed rates of exemplars before and after geometric transformation is shown in Table 1. The similarity overlap contains 467 positive pairs and 1026 negative pairs, which are all passed the classifier before making a transformation. When recognized after geometric transformation, the passed rate of positive pairs is still high, while the passed rate of negative pairs decreases greatly, from 100% to 8.5%.

Table 2 shows detailed passed rates in 8 kinds of geometric transformation. Each passed rate is not so

Table 2: Passed rates of 8 kinds of geometric transformation for 467 positive pairs and 1026 negative pairs.

	NegPass	PosPass	NegRate	PosRate
Up	44	281	4.3%	60.2%
Down	60	318	5.8%	68.1%
Left	81	335	7.9%	71.7%
Right	72	310	7.0%	66.4%
CW Rota	80	343	7.8%	73.4%
ACW Rota	67	351	6.5%	75.2%
Zoom in	12	225	1.2%	48.2%
Zoom out	21	226	2.0%	48.4%
Average	55	299	5.3%	64.0%

high after each kind of geometric transformation for positive pairs, and the average passed rate for positive pairs is only 64.95%, much less than the 95.5% rate in Table 1. That's because all expanded pairs for a positive identities are not so easy to pass altogether, only some of them could. If one of all expanded pairs for one identity has passed, the corresponding identity is accepted. So the passed rate in Table 1 is computed on identity number but not the number of extended pairs. So does the average passed rate for negative pairs.

Experiments show that, geometric transformation makes the positive exemplars passed in the first stage much easier to pass the classifier again than those negative ones. It also makes the reduction of similarity overlap possible, with the greatly decreased passed rate of negative pairs.

4.3 Tests on Open Set Recognition Task

The data set (see Table 3) from FERET consists of 972 frontal face images corresponding to 243 identities and 417 exemplars to 209 persons. In the set of 972 images, 2 exemplars randomly selected from the 4 exemplars of each identity are used for training set. Another exemplar is selected from the remaining two exemplars of each identity to compose gallery set. The last exemplar of each identity is to compose the genuine part of probe set. The other part of probe set is composed by 417 exemplars set. We use different exemplars of the same identities in the training set and the gallery set, for considering the fact in real application: the registered database (gallery set) may update frequently, i.e. a new identity is registered, while the training set seldom changes.

Table 3: Component of the test data set from FERET.

	DupI	Fa	Fb	ID No.
gallery	486	243	243	00002-00907
probe	0	209	208	01001-01209

The training set (486 images, 2 images per identity) generates 486 positive pairs and 236,196 negative pairs for the training process. At any one time, only 3000 negative pairs and all 486 positive pairs are used for training. A new set of 3000 different pairs are chosen from the full set of negative pairs by resampling if the 50 percent false alarm rate is achieved. In our training process, all the negative pairs are discriminated from the positive pairs after 22 stages have been trained. The whole number of weak classifier learned by Adaboost is 1143. The average time to test a 20x20 exemplar is about 200ms.

The performances of GAFR and GTAFR methods is shown in Table 4. The results are got when transformation parameter k equals 2 and the threshold ε equals 0. Hence, the FARs here are maximum of all FARs the two methods can achieve respectively, so do the CCRs.

Table 4: Performances of GAFR and GTAFR, with k=2, ε=0.

	N_p	N_n	N_{pt}	N_{nf}	CCR	FAR
GAFR	243	417	229	367	94.2%	88%
GTAFR	243	417	225	211	92.6%	49.4%

With the method of GAFR, 88 percent negative exemplars pass the classifier and 94.2 percent positive exemplars are accepted. The CCR is approximative to closed set recognition performance using GAFR in (P. Yang and Zhang, 2004). With the method of GTAFR, the FAR is 49.4 percent and the CCR is 92.6 percent. It can be seen, the decrease of CCR is much less than the decrease of FAR.

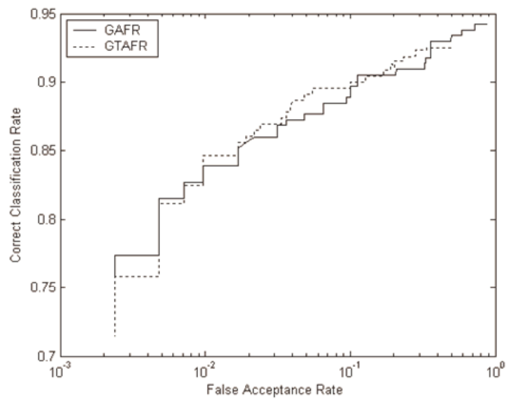

Figure 5: ROC performance curves of GAFR and GTAFR methods.

Results analyzed above are based on the assumption ε=0. In order to assess how FAR affects CCR, ROC curve is shown in Fig. 5, where the maximum FAR and maximum CCR is equivalent to corresponding rates in Table 1. Although the maximum CCR of GTAFR is a little smaller than GAFR, it is not important when system is used in applications, for EER is concerned. Fig. 5 shows that the EER decreases from 11.5% of GAFR to 10.07% of GTAFR. The performance improvement is caused by the decrease of overlap of the similarity distribution. Figs. 6 and 7 show the different similarity distributions by the methods of GAFR and GTAFR respectively. With GAFR method, confidence scores of similarity overlap in the area near 30 percent, and a part of negative pairs distribute in the area between 20∼30 percent. It is difficult to divide positive and negative pairs for the wide overlapped similarity. While with GTAFR method, the confidence scores of negative pairs are greatly decreased and the distance of positive and negative similarity distribution is enlarged. Number of pairs in the overlapped area is much less than that of GAFR.

It is hard to make an accurate comparison between our method and other works, for the different compositions of training and testing database. Generally speaking, compared to ”Open Set TCM-kNN” (88.5% CCR with 6% FAR) (Li and Wechsler, 2005) and Stallkamp et al.'s method (20% EER) (J. Stallkamp, 2007), our GTAFR which achieves 10.07% EER is competitive and even better.

5 CONCLUSIONS

Open set face recognition, due to its wide applications in automated surveillance and security, has been paid more attention recently. Our approach expands the general Adaboost face recognition method and makes it more suitable for open set face recognition task. Geometric transformation is a simple method for exemplar expanding. Inspired by the tendency characteristic of Adaboost cascade classifier, we combine geometric transformation with general face recognition method, which can reduce the overlap of similarity distribution and break up the bottleneck of system performance.

Extensive experimental data from challenging FERET database, shows its efficiency and feasibility. Since the general Adaboost method has not been used for open set task before our works, we test it on the same open set testing database and compare its recognition results with our method. Our method achieves an EER about 10 percent, which is better than the performance of general Adaboost recognition method. Compared to the experimental results of other methods (J. Stallkamp, 2007; Li and Wechsler, 2005), our result is also the better.

The bottleneck of system performance should further be investigated. It is worth noting that although the proposed method could reduce the similarity overlap by increasing CCR and decreasing FAR at the same time, there is still more works to do in this issue.

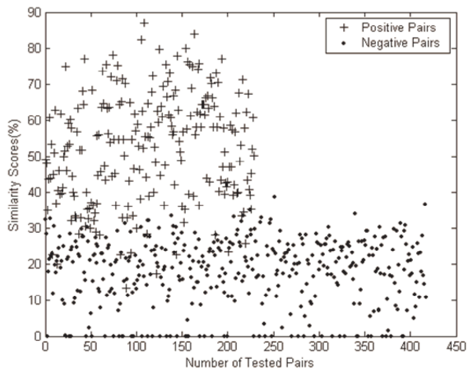

Figure 6: Similarity distribution of positive and negative pairs using GAFR method.

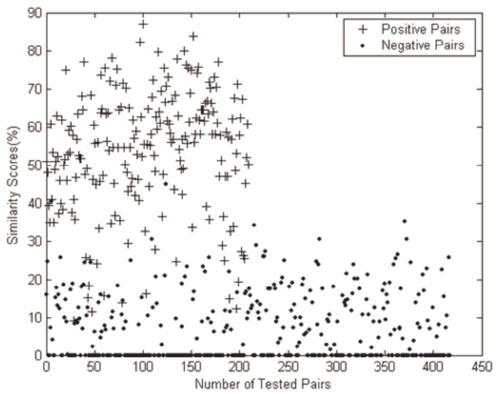

Figure 7: Similarity distribution of positive and negative pairs using GTAFR method.

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