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Original Article

Integrating absolute distances in collaborative representation for robust image classification

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Abstract

Conventional sparse representation based classification (SRC) represents a test sample with the coefficient solved by each training sample in all classes. As a special version and improvement to SRC, collaborative representation based classification (CRC) obtains representation with the contribution from all training samples and produces more promising results on facial image classification. In the solutions of representation coefficients, CRC considers original value of contributions from all samples. However, one prevalent practice in such kind of distance-based methods is to consider only absolute value of the distance rather than both positive and negative values. In this paper, we propose an novel method to improve collaborative representation based classification, which integrates an absolute distance vector into the residuals solved by collaborative representation. And we named it AbsCRC. The key step in AbsCRC method is to use factors a and b as weight to combine CRC residuals res_{crc} with absolute distance vector dis_{abs} and generate a new deviation $r = a \cdot res_{crc} - b \cdot dis_{abs}$, which is in turn used to perform classification. Because the two residuals have opposite effect in classification, the method uses a subtraction operation to perform fusion. We conducted extensive experiments to evaluate our method for image classification with different instantiations. The experimental results indicated that it produced a more promising result of classification on both facial and non-facial images than original CRC method.

Keywords: Sparse representation; Collaborative representation; Integration; Image classification; Face recognition

1. Introduction

Image classification is an crucial technique applied in biometrics like face recognition [1,2] and one of the most significant steps in image classification is to represent or code the images. Proper description or representation of images is the basis of achieving robust image classification results [3,4]. Only with well represented, one subject in the form of the image can be easily distinguished from the others. The basic process of representation-based classification is firstly representing the targeted sample with a linear combination on training samples and then evaluating the dissimilarity to classify the test sample into a closest class. Representation-based classification algorithms play a significant role in face recognition. Among various representation-based classification methods [5–7], sparse representation (SR) and collaborative representation (CR) based classifications are two of most crucial methods that have drawn wide attention [8,9].

Despite face recognition is a convenient biometric technology and has been widely studied, there is still lots of challenge in this area. First, face images may be captured in severe variation of poses, illuminations and facial expressions. Consequently, even the images of one same face may differ significantly, which is likely to corrupt the discrimination. Furthermore, it is another big problem that lack of enough

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training samples for robust face recognition. Some researchers proposed various methods to create more representations of one face to improve the accuracy of face recognition. Gao et al. proposed a virtual face image generation for robust face recognition [10], and Thian et al. also proposed using visual virtual samples to improve face authentication [11]. Recently, Xu et al. proposed to reprocess images with symmetrical samples in sparse representation based image classification [12]. The combination of multiple methods of image classifications is effective for improving the classification accuracy [13]. How to obtain competitive and complementary contributions among multiple descriptions of images is an hot topic. Furthermore, even sparse representation and collaborative representation can be combined together for classification [14]. So integrating multiple classifiers is an effective approach to pursue robust image classification.

This paper proposes a novel method to integrate an absolute distance vector with the coefficient solved by CRC to improve image classification. The basic idea of our proposed method is to calculate an absolute distance vector between the query sample and the training samples when solving the collaborative coefficient, and then integrate the absolute distance vector dis_{abs} for the query sample with the collaborative residuals res_{crc} solved by CRC, with a pair of tuned fusion factors a and b. Therefore a new fusion residuals can be obtained with $r = a \cdot r_{crc} - b \cdot d_{abs}$, which is finally used to perform classification. We tested the proposed method on a number of facial or non-facial datasets and found that it archived higher accuracy than conventional CRC. The paper has the following main contributions to image classification. First, it proposes a novel fusion method to improve CRC. Second, it analyzes and implements a reverse integration on multiple classifiers. Third, it demonstrates an experiment way to find tuned factors for integration on multiple classifiers.

The structure of the following content in this paper is as follows. The related work on SRC, CRC is introduced in Section 2. In Section 3, we describe our proposed method to integrate absolute distances in collaborative representation based classification (AbsCRC). In the next Section 4, we analyze the selection of fusion factors a and b, as well as some classification examples in the experiments. Section 5 conducts our experiments on a couple of popular benchmark datasets, and Section 6 concludes the paper.

2. Related work

Our work is to improve CRC with a novel fusion method. CRC is proposed as an improvement to SRC, therefore we first analyze the work related with conventional SRC before digging into CRC.

2.1. Sparse representation based classification

Sparse representation based classification (SRC) algorithm was proposed by J. Wright et al. [8]. The basic procedure to perform classification based on sparse representation involves two steps, which are first representing the test sample with a linear combination on all training samples and then identifying the closest class based on the minimal deviation.

Assume that there are C subjects or pattern classes with N training samples $x_1, x_2, \ldots, x_n$ and the test sample is y. Let matrix $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,n_i}] \in I^{m \times n_i}$ denote n_i training samples from the ith class. By stacking all columns from the vector of a $w \times h$ gray-scale image, we can obtain the vector to identify this image: $x \in I^m (m = w \times h)$. Each column of A_i is then representing the training images of the ith subject. So any test sample $y \in I^m$ from the same class can be denoted by a linear formula as:

$$y = a_{i,1}x_{i,1} + a_{i,2}x_{i,2} + \cdots + a_{i,n}x_{i,n}, \tag{1}$$

where $a_{i,j} \in I, j = 1, 2, \ldots, n_i$.

And then N training samples of C subjects can be denoted by a new matrix: $X = [X_i, X_2, \ldots, X_C]$. So (1) can be rewritten to a simpler form like:

$$y = X \cdot \alpha \in I^m, \tag{2}$$

where $\alpha = [0, \ldots, 0, a_{i,1}, a_{i,2}, \ldots c, 0, \ldots, 0]^T$ is the sparse coefficient vector in which only entries related with the ith class are not zero. This vector of coefficient is the key factor to affect the robustness of classification. It's noted that SRC using the entire training samples to solve the coefficient.

Next step in SRC is to perform an l_1-norm minimization to solve the optimization problem to pursue the sparsest solution to (2). And this result is used to identify the class of the test sample y. Here we use:

$$(\widehat{\alpha}) = \mathbf{arg\,min}_{\alpha} \|\alpha\|_1, \tag{3}$$

Next, SRC computes the residuals with this representing coefficient vector associated with ith class, that is:

$$\mathbf{r}_{src}(y) = \|y - X_i \cdot \widehat{\alpha}_i\|_2. \tag{4}$$

And finally output the identity of y as:

$$\mathbf{identity}(y) = \mathbf{arg\,min}_i \{\mathbf{r}_{src,i}\}. \tag{5}$$

Some SRC algorithms are also implemented by l_0-norm, l_p-norm $(0 < p < 1)$, or even l_2-norm minimization. Xu et al. [15] exploited the $l_{1/2}$-norm minimization to shrink the sparsity inside the representation coefficient matrix. Allen Y. Yang et al. proposed fast l_1-minimization algorithms called augmented lagrangian methods (ALM) for robust face recognition [16]. Furthermore, many researchers proposed different SRC implementation and improvement, such as kernel sparse representation proposed by Gao et al. [17], an algorithm by Yang and Zhang that using a Gabor occlusion dictionary to raise the computing performance during the process for face occlusion [18], l_1-graph for image classification by Cheng et al. [19], sparsity preserving projections by Qiao et al. [20], and a representation model by prototype together with variation for sparsity based face recognition [21]. Studies also show that the classification accuracy can be also improved by using virtual samples [12,22,23]. All of these are trying to improve the robustness of image classification for face recognition. And it's convinced that sparsity plays a paramount role in robust image classification for face recognition.

2.2. Collaborative representation based classification

Collaborative representation based classification (CRC) was proposed as an improvement and replacement of SRC by Lei Zhang et al. [9,24,25]. It's approved that most literature on SRC, including [8], may emphasize too much on the significance of l_1-norm sparsity in image classification, while the role of collaborative representation (CR) is somehow ignored [9]. As we know that CR is involving all contribution from every single training sample to represent the test sample y. Because it's fact that different face images share some common features helpful for classification, which is called nonlocal sample. CRC can learn this nonlocal strategy to output more robust face recognition.

Let us note $X=[X_1,X_2,\ldots,X_C]\in I^{m\times N}$, and then the test sample $y\in I^m$ can be represented with:

$$y=a_1x_1+a_2x_2+\cdots+a_Nx_N. \tag{6}$$

And then use the regularized least square method to collaboratively represent the test sample using X with low computational burden. That is:

$$\left(\widehat{\beta}\right)=\mathbf{arg\,min}_\beta\left\{\|y-X\cdot\beta\|_2^2+\lambda\cdot\|\beta\|_2^2\right\}, \tag{7}$$

where λ is a regularization parameter, which makes the least square solution stable and introduces a better enough sparsity to the solution than l_1-norm. So the solution of CR in (7) can be derived as:

$$\widehat{\beta}=\left(X^T\cdot X+\lambda\cdot I\right)^{-1}X^T. \tag{8}$$

Let $P=\left(X^T\cdot+\lambda\cdot I\right)^{-1}X^T$, so that we can just simply project the test sample y onto P and get this formula:

$$\widehat{\beta}=P\cdot y. \tag{9}$$

At this step, the classification is performed based on the coefficient $\widehat{\beta}$ with the class specific representation residual $\left\|y-X_i\cdot\widehat{\beta}_i\right\|$. Hereby $\widehat{\beta}_i$ is the coefficient vector related with class i and computed with:

$$\widehat{\beta}_i=\sum X_i\cdot\widehat{\alpha}_i, \tag{10}$$

where $\widehat{\alpha}_i$ is the coefficient vector to one single sample belonging to the same class, which is used in SRC [8] to perform classification.

So that it computes the regularized residuals by:

$$\mathbf{r}_{crc}=\left\|y-X_i\cdot\widehat{\beta}_i\right\|_2\Big/\left\|\widehat{\beta}_i\right\|_2. \tag{11}$$

Finally, it outputs the identity of the test sample y as:

$$\mathbf{identity}(y)=\mathbf{arg\,min}_i\{\mathbf{r}_{crc,i}\}. \tag{12}$$

In this way, CRC involves all training samples to represent the test sample, which is considered as an improvement to conventional SRC [9,24,25]. Also, there are a host of methods proposed to optimize CRC. Zhang et al. proposed to integrating globality from other samples with locality in current sample to generate robust classification [26]. Xu et al. applied transfer learning algorithm into sparse representation [27]. Fusion of multiple classifiers is also applied in CRC [28]. And recently CRC was reinterpreted with a probabilistic theory [29]. CRC still has large space to improve, especially on the collaborative coefficient for test sample.

3. Our method

Based on nearest feature line (NFL) and nearest feature plane (NFP) [30,31], we can calculate the sum of representation coefficients from all samples in one class and use them to represent to weight of one class. Then the test sample is classified into one class with maximal weight value. The greater the sum value is, the more contribution is produced from that class.

From the procedures of SRC and CRC, We can infer that l_2-norm sparse coefficient $\left\|\widehat{\beta}_i\right\|_2$ contains some crucial discrimination clue for classification. In order to generate a more promising result, this is probably a candidate part where we should pay more efforts to. Here comes our proposed method: firstly using absolute value of coefficient instead of original value to obtain the distance between the test sample and each class, and then integrating the distance vector with the one from CRC for classification. Hereafter the schema of proposed AbsCRC is demonstrated.

3.1. Solving distance with the absolute values

Instead of directly solving coefficient $\widehat{\beta}_i$ for each class with the sum of all coefficients from all samples with (10), we turn to sum absolute value of all coefficients to calculate the whole distance between the test sample and the class:

$$\mathbf{d}_i=\sum|\widehat{\alpha}_i|. \tag{13}$$

And this distance vector can used to identify a class most relevant with the test sample. In this distance vector, however, the bigger value indicates the test sample is more relevant with the class represented by the training samples. So that the role by this absolute distance vector d_i is opposite with the one by collaborative representation residuals r_i.

For comparison, we here use the maximal value in this vector to identify a class most relevant with the test sample y:

$$\mathbf{identity}(y)=\mathbf{arg\,max}_i\{\mathbf{d}_i\}. \tag{14}$$

However, when the new residuals are used to directly perform classification, robust classification cannot be obtained. This was demonstrated in our experiments, as shown in Section 5.

3.2. Integrating absolute residuals with original ones

While using absolute residuals alone cannot produce a comparable classification with original ones in CRC, integrating absolute with original residuals can bring a more promising reaction. In the integration, the residuals by CRC is integrated with the absolute distance vector by different weights a and b respectively. Therefore, we can obtain the new residuals with:

$$\mathbf{r}_i = a \cdot r_{crc,i} - b \cdot d_i. \quad (15)$$

It's noted that usually a can be assigned value of 1, that is $a = 1$, for simplicity. And then using different value of b can still reflect the weight of absolute distance. Furthermore, since the absolute distance plays an opposite role in classification, in (15) we use subtraction to combine the absolute distance.

Finally, it outputs the identity of the test sample y with the new residuals:

$$\mathbf{identity}(y) = \mathbf{arg\,min}_i\{\mathbf{r}_i\}. \quad (16)$$

4. Analysis

In this section, we use some experiment cases to demonstrate the rationale and effects of our proposed AbsCRC method. Indeed, the absolute distance vector alone does not bring good enough helps on image classification or face recognition, by which the classification results can not match the results by conventional CRC in most cases. However, when integrating the absolute distance vector with the residuals from CRC, the fusion residuals can produce outstanding classification results.

The absolute distance vector may help stabilize the representation coefficients by CRC. This is the most crucial contribution in our AbsCRC method. On the other hand, the fusion process is affected by the selection of weighted factors b. So our second effort is to find out optimized weighted factors for robust image classification or face recognition.

Fig. 1 shows the CRC residuals, absolute distances and fusion residuals in one experiment case, which was run on ORL face database with first 6 images as training samples and the rest as test samples (See subsection 5.3). And this group of residuals are for a test sample at number 113 position, which is the first test sample of twenty-ninth class (number 4 * 28 + 1 = 113 sample). We can see from the Fig. 1 that the fusion residuals (green) are affected by the absolute distance vector and slightly flatter than the original residuals by conventional CRC (yellow).

In this experiment case, with factor of $b = 0.1$ (See Table 3), both CRC and ABS were failed to classify the number 113 test sample into a right class, while only AbsCRC produced a right answer, as shown in Fig. 2.

Consequently, our experiments have taken into account the weighted factor b for different classification cases. And in a glut of benchmark datasets, we are managed to choose a group of parameters that help AbsCRC generate an optimized result. The next Section 5 will demonstrate all the experimental results.

5. Experimental results

In this section, we will demonstrate our experimental results on some popular visual benchmark datasets. Extensive experiments were conducted on these datasets to evaluate the classification accuracy of conventional CRC, absolute distance only (ABS) and our AbsCRC method, as well as the selections of fusion factors a and b. The chosen benchmark datasets include Caltech Faces [32], Caltech Leaves [32], ORL [33], FERET [34], CMU Faces [35], and Senthil IRTT Face Database [36].

On each benchmark database, we respectively run experiments with different number of training samples, as well as

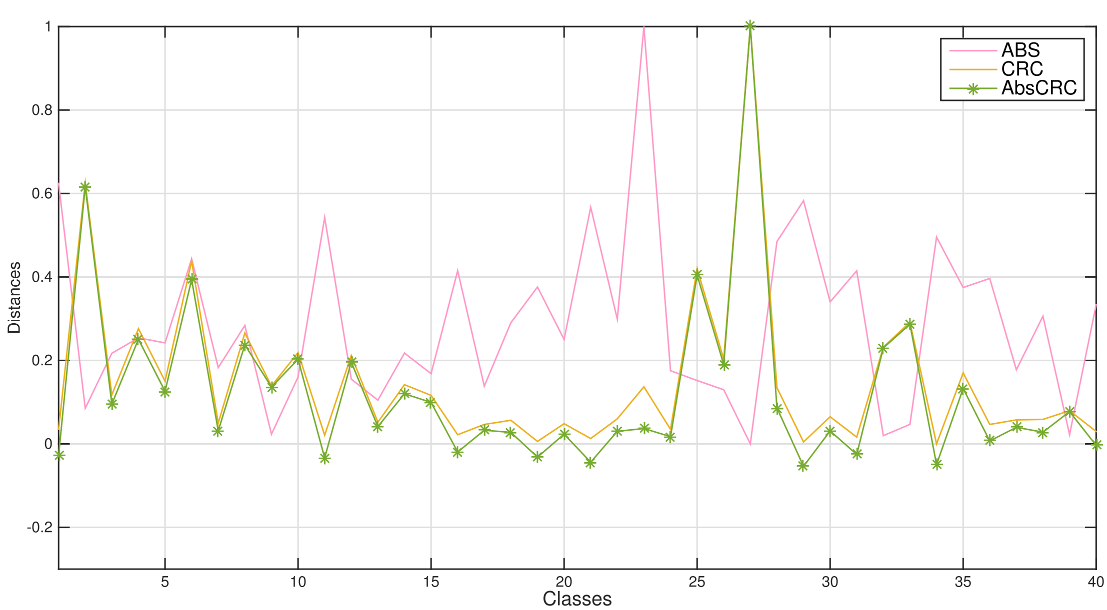

Fig. 1. Residuals for a test sample in ORL face database.

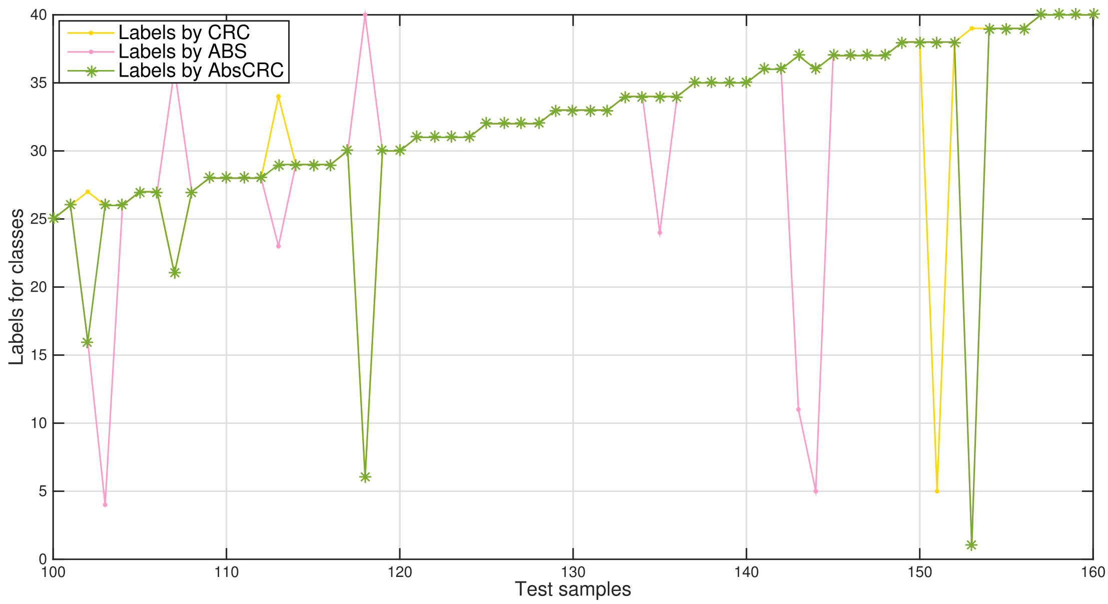

Fig. 2. Labels classified for a test sample in ORL face database.

different integration factors a and b. For simplicity, we keep $a = 1$ and use different value of b to reflect the weights of two coefficients. In our experiments, we found that when CRC outperforms ABS, it's better to assign a value less than one to b, that is $b < 1$; on the contrary, usually $b > 1$ usually produces more pleasuring result when ABS outperforms CRC. However, there are still some exceptional experiments cases. So our experiments also paid efforts to seek a optimal fusion factor b. The following subsections will demonstrate the samples, steps, factors and results in every experimental case, as well as our discussion on the results. The experimental results indicate that in most cases the AbsCRC is managed to produce higher accuracy of classification than CRC.

5.1. Experiments on Caltech Faces dataset

The Caltech Faces dataset is a frontal face dataset collected by Markus Weber at California Institute of Technology [32]. There are 450 facial images in this dataset, which is all in size of 896*592 pixels and JPEG format. These pictures were taken from 27 or so unique people under with different lighting, expressions and backgrounds. We resized each image into half-scale of 488*296 pixels to reduce computing complexity. Furthermore, we selected only 19 subjects with more that 10 samples in our experiments to fulfill the experimental requirements that there are 8 training samples at least in every subject. In out experiments, however, it is not necessary to use all three dimensions data in these colored images. Therefore we converted these original colored images to gray scale before running our tests.

For each subject, we successively took 1 to 8 face images as training samples and the rested as test samples. We evaluated the wrong classification rates of CRC, ABS and AbsCRC algorithms, as well as different weight factor b. The classification results are shown in Table 1. In most experimental cases, AbsCRC unexpectedly outperformed CRC in this dataset. The error rates by ABS only are also listed in the table for comparison. The most promising case is the one using 7 training samples and $b = 0.2$, in which AbsCRC outperforms both CRC and ABS and the error rate drops down to 33.33%. On the whole, experimental results on this dataset demonstrated that our AbsCRC gained an excellent improvement onto conventional CRC in image classification.

Table 1
Improvements to CRC on Caltech Faces dataset.

Trainings	b	Error rates			Improvements	
		CRC	ABS	AbsCRC	⇓ CRC	⇓ ABS
1	0.6	0.8480	0.8363	0.8363	1.38%	0.00%
2	0.001	0.6908	0.7368	0.6908	0.00%	6.25%
3	0.6	0.6767	0.6767	0.6617	2.22%	2.22%
4	10	0.6579	0.6140	0.6140	6.67%	0.00%
5	1.5	0.5368	0.5263	0.4632	13.73%	12.00%
6	0.4	0.4211	0.4868	0.4079	3.13%	16.22%
7	0.2	0.3509	0.4912	0.3333	**5.00%**	**32.14%**
8	0.001	0.3421	0.4474	0.3421	0.00%	23.53%

5.2. Experiments on Caltech Leaves dataset

Caltech Leaves dataset [32] is also taken around Caltech by Markus Weber from California Institute of Technology. There are 186 images of leaves against different backgrounds and with approximate scale normalization. All images are also in JPEG format and in size of 896*592 pixels as well. We again resized them to half scale. At this time, we selected only 7 subjects with more that 10 samples in our experiments so that there are 8 training samples at least in every subject. Because it is not necessary to use all three dimensions data in these colored images, we converted these original colored images to gray scale before running our tests.

The results for this group of experiments are shown in Table 2. In this non-facial dataset, AbsCRC again generated amazing results. As we known that CRC is a method specific for face recognition, so it fell behind ABS in almost all cases. However, AbsCRC is managed to produce a more pleasuring accuracy in many cases. The most promising case is the one using 8 training samples and $b = 0.2$, in which AbsCRC outperforms both CRC and ABS by 16.67% and the error rate drops down to the lowest level of 35.71% (See the last row with start mark). This group of experiments demonstrated that AbsCRC works well in non-facial image classification.

5.3. Experiments on ORL face database

ORL face database [33] is a small database that includes only 400 facial images taken from 40 folks and every single class provides only 10 distinct face images. The facial images were captured at different conditions for every subject like times, lighting, facial expressions (open or closed eyes, smiling, or not smiling), and facial details (glasses or no glasses). Besides, these images were taken against a dark consistent background while the folks were in an upright, frontal position. For simplicity, we resized all the face images to 56*46 pixels. We designedly renamed all image files to filenames with ordered numbers in 3 digits, which are elegant to reflect the right position of classes in experiments.

We respectively took first 1 to 8 picture(s) of each subject as source training samples and used the other face images as test samples. We evaluated the classification failure rates by all algorithms. The classification results are outstanding and in a very low error rates. Table 3 shows the detailed error rates as well as the improvements by three algorithms. The most promising result to AbsCRC was generated on the case of using 8 training samples, in which AbsCRC outperformed CRC up to 50.00% when $b = 1.3$. And the classification accuracy reaches an amazing level of 95.00%. Furthermore, AbsCRC produces higher accuracy on all cases with at least 4 training samples.

Table 2
Improvements to CRC and ABS on Caltech Leaves dataset.

Trainings	b	Error rates			Improvements	
		CRC	ABS	AbsCRC	⇓ CRC	⇓ ABS
1	0.001	0.6349	0.6349	0.6349	0	0
2	0.1	0.5893	0.5893	0.5714	3.03%	3.03%
3	0.001	0.5714	0.5918	0.5714	0	3.45%
4	0.1	0.5714	0.6429	0.5476	4.17%	14.81%
5	1.1	0.5714	0.5143	0.5143	10.00%	0
6	100	0.5714	0.3929	0.3929	31.25%	0
7	2.0	0.5238	0.4286	0.4286	18.18%	0
8	0.2	0.4286	0.4286	0.3571	**16.67%**	**16.67%**

Table 3
Improvements to CRC and ABS on ORL face database.

Trainings	b	Error rates			Improvements	
		CRC	ABS	AbsCRC	⇓ CRC	⇓ ABS
1	0.001	0.3194	0.3278	0.3194	0	2.54%
2	0.001	0.1656	0.1938	0.1656	0	14.52%
3	0.001	0.1393	0.1786	0.1393	0	22.00%
4	0.2	0.1083	0.1500	0.1042	3.85%	30.56%
5	0.2	0.1150	0.1500	0.1050	8.70%	30.00%
6	0.9	0.0813	0.1250	0.0688	15.38%	45.00%
7	0.7	0.0833	0.0917	0.0750	10.00%	18.18%
8	1.3	0.1000	0.0625	0.0500	**50.00%**	**20.00%**

5.4. Experiments on FERET face database

The FERET benchmark database [34] is one of the biggest visual databases. In FERET database, each subject has a group of five to eleven images including two frontal views (fa and fb) and one more frontal image by a different facial expression. We chose to test on 200 subjects in the database, which means this group of experiments were running on a scale of 1400 face images and seven samples in each subject. In our experiments, all images are renamed to an ordered number filename. With this type of ordered number filenames, we can easily figure out the right answer in the classification algorithm.

Since there are only 7 samples in each subject, we respectively used first 1 to 5 images as training samples and the remaining images as test samples. This group of experiments generated a pleasure classification results. Though the improvement by the new algorithm is not so outstanding as that on the other databases, AbsCRC still slightly outperforms conventional CRC. The detailed improvements by AbsCRC are shown in Table 4. We can see that AbsCRC still outperformed CRC up to 7.14% when using 5 training samples with $b = 0.4$. And the error rate on classification is at a very low level of 29.25%.

5.5. Experiments on CMU face images

The CMU face images [35] consists of 640 black and white face images of people taken with varying pose (straight, left, right, up), expression (neutral, happy, sad, angry), eyes (wearing sunglasses or not), and size. All images are in PGM format and grouped by the name of specific subject. There are 20 subjects in total and up to 96 images in some subjects, while some subjects contains only images less than others. So

Table 4
Improvements to CRC and ABS on FERET face database.

Trainings	b	Error rates			Improvements	
		CRC	ABS	AbsCRC	⇓ CRC	⇓ ABS
1	0.001	0.5567	0.5783	0.5567	0	3.75%
2	0.4	0.4160	0.4340	0.4070	2.16%	6.22%
3	1.8	0.5563	0.5563	0.5288	4.94%	4.94%
4	0.2	0.4467	0.4800	0.4367	2.24%	9.03%
5	0.4	0.3150	0.3600	0.2925	**7.14%**	**18.75%**

we chose to select 54 images that exist in all subjects as experimental samples. That means there are 20*54 = 1080 images used in this group of experiments.

In this group of experimental cases, we still took first 1 to 8 images as training samples and the rest images as test samples. Table 5 shows the detailed results of classification. The most promising case is the one with 7 training samples and $b = 0.1$. Though AbsCRC only outperforms CRC by 4.55%, the classification accuracy reaches 91.06%. We can see that ABS alone did not perform as well as CRC, but it pushes CRC up to a higher level by a simple fusion.

5.6. Experiments on Senthil IRTT face database

The Senthil IRTT Face Database Version1.2 [36] contains both color and gray scale faces from IRTT students. There are 100 facial images for 10 IRTT young female students around 23–24 years, and each has 10 facial samples. The color images along with background are captured with a pixel resolution of 480*640 and their faces are cropped to 100 × 100 pixels. All facial images are labeled with the number of subject and sample. This database is relatively smaller than others, so that the experiments run fast.

Using 1 to 8 training samples, our experiments run fast and smoothly. The most promising case for AbsCRC is the one using 6 training samples with $b = 0.1$. The improvement rate from AbsCRC to CRC and ABS reaches 20% and the classification accuracy reaches a high level of 90.00%. Again, though not performing as well as CRC, ABS pushes CRC up to higher level with fusion.

5.7. Discussion

In the all 6 datasets, there are 5 facial datasets and one non-facial datasets. The experiments showed that integrating ABS into face recognition method CRC helps improve the classification robustness of CRC, which is effective in both facial and non-facial image classification. Besides we can find some other useful hints for image classification when applying absolute distance in collaborative representation.

Absolute distance based classification might be not stable enough in face recognition. As shown in the detailed results from Tables 1, 3–6, the results by ABS in most cases did not match the ones by original CRC. While Table 2 demonstrated that ABS works better than CRC on non-facial image classification.

Table 5
Improvements to CRC and ABS on CMU face images.

Trainings	b	Error rates			Improvements	
		CRC	ABS	AbsCRC	⇓ CRC	⇓ ABS
1	0.001	0.2896	0.3094	0.2896	0	6.40%
2	0.1	0.2923	0.3115	0.2904	0.66%	6.79%
3	0.001	0.3098	0.3176	0.3098	0	2.47%
4	0.1	0.1390	0.2130	0.1320	5.04%	38.03%
5	0.1	0.1398	0.2306	0.1327	5.11%	42.48%
6	0.1	0.1427	0.2365	0.1375	3.65%	41.85%
7	0.1	0.0936	0.3011	0.0894	**4.55%**	**70.32%**
8	0.01	0.0913	0.3467	0.0902	1.19%	73.98%

Table 6
Improvements to CRC and ABS on Senthil IRTT face database.

Trainings	b	Error rates			Improvements	
		CRC	ABS	AbsCRC	⇓ CRC	⇓ ABS
1	5.0	0.8111	0.8111	0.8000	1.37%	1.37%
2	0.6	0.8000	0.8375	0.7750	3.13%	7.46%
3	0.1	0.6714	0.7429	0.6571	2.13%	11.54%
4	0.3	0.4833	0.5167	0.4333	10.34%	16.13%
5	0.2	0.1400	0.1800	0.1200	14.29%	33.33%
6	0.1	0.1250	0.1250	0.1000	**20.00%**	**20.00%**

The number of training samples still matters. As shown in Tables 1–6, the more training samples we used in classification, the higher classification accuracy we can obtain. This is truth in both facial and non-facial datasets.

One-training-sample issues exists as usual. Almost in all face databases, the results when using only one training sample are usually at the lowest accuracy, even some of them produced zero improvement. Such unstable only-one-training-sample case is an common issue in face recognition, but it can be mitigated with a host of methods, like [22,37,38] and so forth.

6. Conclusion

This paper proposed a novel absolute collaborative representation based classification (AbsCRC) method for robust image classification. When solving the representation coefficient CRC, we calculate the sum of the absolute distance between the test sample and the training samples at the same time. And then this absolute distance vector is integrated with original collaborative coefficient to generate a more promising classification. In the fusion, a tuned factor b is involved to adjust the weights from both distance vectors to output the best classification. Extensive experiments were conducted on a couple of facial and non-facial benchmark databases, and the results demonstrate that AbsCRC outperforms state-of-the-art CRC in most of cases.

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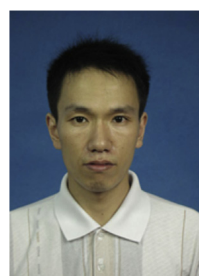

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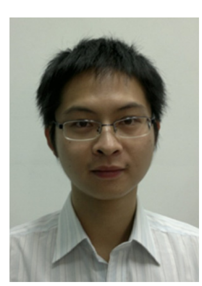

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