Face detection method based on nonlinear composite correlation filters

Everardo Santiago-Ramírez[1], José-Ángel González-Fraga[1], Everardo Gutiérrez-López[1], Omar Álvarez-Xochihua[1], and Sergio-Omar Infante-Prieto[2]

[1] Facultad de Ciencias, Universidad Autónoma de Baja California, Carretera Transpeninsular Ensenada-Tijuana Núm. 3917, Colonia Playitas, Ensenada, Baja California, C.P. 22860
{everardo.santiagoramirez,angel_fraga,everardo.gutierrez,aomar}@uabc.edu.mx

[2] Facultad de Ingeniería, Arquitectura y Diseño, Universidad Autónoma de Baja California, Carretera Transpeninsular Ensenada-Tijuana Núm. 3917, Colonia Playitas, Ensenada, Baja California, C.P. 22860
sinfante@uabc.edu.mx

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Abstract. Face detection is an important first step in a fully automatic face processing system. Current algorithms are able to detect faces that are easily distinguishable. However, most of these algorithms perform poorly when used to process images taken under conditions with non-uniform illumination and the face present variations in pose. In this paper, we present a face detection algorithm that uses nonlinear composite correlation filters, designed with strong classifiers. For the design of strong classifiers, a set of transformations were applied to original training images. In order to improve the discrimination capacity and robustness in conditions with homogeneous and structured backgrounds, the training images for the filters were selected by an algorithm from a face database. The performance of the proposed algorithm was evaluated in terms of its ability to determine the location of a single face under conditions with non-uniform illumination and slight variations in pose.

Keywords:
Face detection, nonlinear composite correlation filters, correlation pattern recognition

1 Introduction

The need for reliable face detection systems, that function in both indoor and outdoor environments has caught researchers and technologists' interest in developing facial-distortion invariant algorithms. While face detection has a wide range of applications, its principal application has been in automatic face recognition systems. The accuracy of a face detection algorithm is important for the performance of subsequent face processing tasks in a system. Given an arbitrary image, the objective of face detection is to determine whether or not any faces are found in the image, and, if detected, to return the location and dimension of the face [1]. This can be achieved using the information provided by several cues, such as skin color (for color images), movement (for faces appearing in a video), face or head shape, facial appearance, or a combination of these parameters [2].

Face detection methods can be classified into four main categories [1]: 1) Knowledge-based methods, which encode human knowledge about face components; 2) feature invariant approaches, which are mainly based on the face's structural features; 3) template matching methods, where several previously stored standard patterns are correlated with an input image in order to detect a face and; 4) appearance-based methods, where facial models are learned from a set of training images which should capture the representative variability of facial appearance. The most successful face detection methods are based on appearance and are able to detect all faces in an image with great accuracy, independently of their position, dimension, orientation, age and expression [2].

However, these face detection algorithms only perform well under conditions where the facial regions are easily distinguishable. Composite correlation filters are able to combine the characteristic of both template matching and appearance based methods as they use both face shape (structure) and face content (appearance). A composite correlation filter is designed by combining training images that are representative of the expected distortions for the reference object. For this reason, the performance of the composite filters depends largely on an appropriate selection of training images. A face detection method that employs correlation filters does appear in the literature [3]. An important aspect to consider in the use of this method is that it requires a large amount of training images, however, it not consider a method for selecting solely the most suitable face images.

This paper presents a face detection algorithm based on nonlinear composite correlation filters which was designed using strong classifiers that emphasize facial features. Given a face database, a simple algorithm selects only those face images that produce a sharp and high peak for the training set. In order to increase the amount of data and model highly representative distortions, different versions of the training set were obtained by applying image transformations. Each version of the training set was used to design strong classifiers, which were then used to design a robust nonlinear composite correlation filter for detecting faces in scene images with homogeneous and structured backgrounds.

The rest of the paper is organized as follows. Section 2 presents the theoretical foundation for composite correlation filters. Section 3 then describes the proposed face detection method. The results of the experiment and a discussion of them are presented in Section 4. Finally, Section 5 presents the main conclusions of this work.

2 Composite correlation filters

Correlation pattern recognition (CPR) is based on selecting or creating a reference signal $h(x, y)$, called a correlation filter, and then determining the degree of similarity between the reference and test signals [4]. Correlation filters can be designed in either the spatial or frequency domain. The correlation process using the Fourier Transform (FT) is given by:

$$g(x, y) = \mathcal{F}^{-1}\{S(u, v) \cdot H^*(u, v)\}, \tag{1}$$

where $g(x, y)$ is the correlation output, $\mathcal{F}^{-1}$ is the inverse Fourier transform, and $S(u, v)$ and $H(u, v)$ are the Fourier transforms of the test signal $s(x, y)$ and and reference signal $h(x, y)$, respectively. The symbol $\cdot$ indicates that S and H are multiplied element by element, and $*$ represents the complex conjugate of H. In ideal circumstance, when $s(x, y)$ contains multiple objects that are similar to $h(x, y)$, $g(x, y)$ should exhibit large correlation peaks for each object in the scene that matches with $h(x, y)$.

The most basic correlation filter is the Matched Filter (MF), which is robust in recognizing reference images affected by additive white noise [5]. However, it is very sensitive to distortions such as rotation and scale. MF is given by:

$$H(u, v) = \alpha T^*(u, v), \tag{2}$$

where $T^*(u, v)$ is the is the FT of the reference image $t(x, y)$.

2.1 Nonlinear composite filter

A Synthetic Discriminant Function (SDF) filter is a linear combination of Matched Filters [6]. This filter is designed using a training set T composed images containing the principal distortions expected for the reference image, and is, therefore, robust in recognizing an object that presents distortions similar to those found in T.

Let $T = \{t_1(x, y), t_2(x, y), ..., t_N(x, y)\}$ be the training image set and $\boldsymbol{x_j}$ the column-vector form of $t_j(x, y)$. $\boldsymbol{x_j}$ is created by lexicographic scanning, in which each image is scanned from left to right and from top to bottom. Each vector is a column of the training data matrix $X = [\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_N}]$. The SDF correlation filter is given by:

$$\mathbf{h} = X(X^+X)^{-1}\mathbf{u}, \tag{3}$$

where $+$ is the complex conjugate transpose and $\mathbf{u} = [u_1, u_2, ..., u_N]^+$ is a vector of size $N \times 1$ that contains the expected values at the origin of the correlation output for each training image. Typical values for u are 1 for images belonging to the true class and 0 for those in the false class. The -1 indicates the inverse of the matrix. Although this filter is tolerant to distortions, the correct location of the object is complicated by the wide peak produced in the output correlation. Therefore, the FT of each training image can be filtered with the $kth - Law$

nonlinear factor, as shown in expression 4, thus improving the sharpness of the peak.

$$\hat{T}_i^k(u,v) = |\hat{T}_i(u,v)|^k \exp(i\varphi(u,v)), \tag{4}$$

where $0 < k < 1$ is the nonlinear factor. $\hat{T}_i(u,v)$ is the FT of $t_i(x,y)$, $|\hat{T}_i(u,v)|$ is the module of $\hat{T}_i(u,v)$, while $\varphi(u,v)$ is its phase. As can be observed, the nonlinearity factor raises the magnitude of the Fourier spectrum to the kth power, while the information of the phase remains intact. In the correlation process, the same nonlinear factor k used in the filter training must be applied to the test image. Applying the nonlinear factor to training images for the SDF filter in expression 3, a nonlinear composite correlation filter is given by [7]:

$$\mathbf{H}^{\mathbf{k}} = X^k((X^k)^+ X^k)^{-1}\mathbf{u}. \tag{5}$$

2.2 Average of synthetic exact filters

Let $t_i(x,y) \in T$ be the training image and $g_i(x,y)$ its desired correlation output, which can be synthetically generated by a Gaussian functions as follow:

$$g_i(x,y) = \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{\sigma^2}\right), \tag{6}$$

where σ^2 is the radius of the Gaussian at the center of the object. Each pair $t_i(x,y)$, $g_i(x,y)$ is used to construct an exact filter with the following expression:

$$H_i^*(u,v) = \frac{G_i(u,v)}{\hat{T}_i(u,v)}, \tag{7}$$

where the division is element by element. $G_i(u,v)$ and $\hat{T}_i(u,v)$ are the FT's of $g_i(x,y)$ and $t_i(x,y)$, respectively. The ASEF filter is obtained by averaging $N = |T|$ exact filters [3], such as is shown in the following expression:

$$H(u,v) = \frac{1}{N}\sum_{i=1}^{N} H_i^*(u,v). \tag{8}$$

3 Face detection method using nonlinear composite filters

The algorithm proposed in this work exploits both face shape and face content in a nonlinear composite correlation filter that contains enough information to detect faces in a scene. This algorithm comprises of the following steps: *Training set selection*, *nonlinear composite correlation filter design* and *face detection*.

3.1 Training set selection

The success of face detection by correlation filters depends largely on the training set T, which has to describe the expected distortions of a human face. This set T must be small enough for computational convenience and contain only those images suitable for the design of a filter for reliable face detection. A simple correlation-based strategy, described by Algorithm 1, was designed for selecting the suitable images for filter design.

Algorithm 1: Training set selection.

Data: Whole face images set F_{DB}, initial images training S_f, threshold value τ
Result: Training set T

$H(u, v) \leftarrow$ Design initial filter with S_f
$N \leftarrow 1$
$T \leftarrow \{\}$
while $N \leq |F_{DB}|$ **do**
  $t_N(x, y) \leftarrow$ Read $t_N(x, y)$, such that $t_N(x, y) \in F_{DB}$
  $\hat{T}(u, v) \leftarrow \mathcal{F}\{t_N(x, y)\}$ // $\mathcal{F}$ is the Fourier transform
  $\hat{T}^k(u, v) \leftarrow |\hat{T}(u, v)|^k \exp(j * \varphi(u, v))$
  $g(x, y) \leftarrow \mathcal{F}^{-1}\{\hat{T}^k(u, v) \cdot H^*(u, v)\}$
  $psr \leftarrow PSR(g(x, y))$
  if $psr \geq \tau$ **then**
    $T \bigcup t_N(x, y)$
    $H(u, v) \leftarrow$ Update II using $t_N(x, y)$
  $N \leftarrow N + 1$

Algorithm 1 receives a face images database as first parameter. As the goal is to maximize the performance of a filter which averages the training images (see Subsection 3.2), the database must contains as many images as possible. The second argument S_f contains some ideal images for building an initial filter. So, a first arbitrary face image can be included in the training set only if it is similar to the initial filter. The arbitrary face image is correlated with the filter $H(u, v)$ and, if its sharpness is equal to or greater than the third argument τ, then it is added to the training set T and used to update $H(u, v)$. Both the initial and updated filter $H(u, v)$ in Algorithm 1 are designed by an average accumulator function $H_i(u, v) = \frac{N-1}{N} H_{i-1}(u, v) + \frac{1}{N}\hat{T}^k_{current}(u, v)$. Where $\hat{T}^k_{current}(u, v)$ is the FT of a face image with $kth-Law$ nonlinear filtering. The Peak-to-Sidelobe Ratio (PSR) measures the peak sharpness in the correlation output; therefore, the larger the PSR the more likely the test image belongs to the true class [4]. The threshold value τ is the minimal PSR that assures that an image region corresponds to a face. The threshold was experimentally determined and fixed at $\tau = 10$. The peak-to-sidelobe ratio (psr) measures the number of standard deviations at which the peak is found to be above the mean value in the correlation output. The PSR metric is given by the expression 9, where μ_{area} and σ_{area} respectively are the mean and standard deviation of some area or neighborhood around, but not including, the peak.

$$psr = \frac{(peak\ value - \mu_{area})}{\sigma_{area}}. \tag{9}$$

3.2 Nonlinear composite filter design

In order to produce a sharp and high peak on a less noisy correlation plane, our proposed algorithm is based on the Nonlinear Composite Correlation Filter and ASEF filters. An exact filter is considered as a weak classifier because it only matches the training image. However, averaging many weak classifiers, as ASEF filters do, yields a robust classifier that will match with many objects of the same class, even if they do not belong to the training set. For the modeling of some principal distortions not contained in the training set, each training image for Algorithm 2 is processed by the following operations. For in-plane rotation, each image is rotated +15 and −15 degrees. Zero mean Additive White Gaussian Noise (AWGN), with variances of 0.1 and 0.2, was added to each face image for noise modeling. There are two main face shapes, rounded or elongated, which is an important issue that must be taken into account by approaches based on template such as that which is presented in this paper. For this reason, the images in T were scaled in width to $\frac{2}{3}$ and $\frac{3}{4}$. Finally, each training image was flipped from left to right. These image transformations are summarized in Table 1.

Table 1. Image transformations to model distortions not contained in T.

Number	Image transformation
0	Original images
1	In-plane rotation of 15 degrees
2	In-plane rotation of −15 degrees
3	AWGN with mean 0 and variance 0.1
4	AWGN with mean 0 and variance 0.2
5	Scale in width to $\frac{2}{3}$
6	Scale in width to $\frac{3}{4}$
7	Flipping left to right

The input argument for Algorithm 2 is the training set T generated by Algorithm 1, while the output is a simple Nonlinear Composite Correlation Filter. First, eight training sets are derived from the application to the input training set of the transformations discussed in Table 1. Second, each training set generated is used to build a strong classifier $H_{ASEF}(u, v)$, based on the design of an ASEF filter. For computational convenience, ASEF filters take on the original size of the images and are then synthesized in the spatial domain to enable a

Algorithm 2: Nonlinear composite correlation filter design.

Data: training set T
Result: Correlation filter $H(u, v)$ for face detection
$T_{trainset} \leftarrow \{\}$
for $i \leftarrow 0$ **to** 7 **do**
    $T_i \leftarrow$ Apply the *ith* image transformation of Table 1 to images in T
    $H_{ASEF}(u, v) \leftarrow$ Design an ASEF filter (strong classifier) with equation 8 using T_i as training set
    $h_i(x, y) \leftarrow \mathcal{F}^{-1}\{H_{ASEF}(u, v)\}$
    $h_i^{'}(x, y) \leftarrow$ Padding $h_i(x, y)$ with $mean\{h_i(x, y)\}$
    $T_{trainset} \bigcup h_i^{'}(x, y)$
$H(u, v) \leftarrow$ Design a nonlinear composite correlation filter with equation 5 using the training set $T_{trainset}$.

padding operation with their mean values. Finally, each ASEF filter in the spatial domain is taken as training datum in the design of a nonlinear composite filter $H(u, v)$, as described in section 2.1.

3.3 Face detection algorithm

This work used a bank of filters of different dimensions, which is correlated with an input scene image $s(x, y)$ for detecting human faces. This proposal is composed of two main steps: 1) Construction of the bank of nonlinear composite correlation filters and 2) the face detection algorithm. Correlation filters for face detection are designed in the step 1, and must contain enough facial information to produce a high, sharp peak centered at the face location. These filters are stored in order to use them each time that face detection is performed on a test image. Step 2 corresponds to the face detection algorithm, which is given by Algorithm 3. A given test image $s(x, y)$ is improved by function $s^{'}(x, y) \leftarrow preprocessing(s(x, y))$, which performs the following operations. First, retina filtering is applied to images for improving the quality of images with non-uniform illumination [8]. Although we could use logarithmic transformation for this first operation, experimentally it was observed that retina filtering is best for retrieving the edge information in a scene image. An energy normalization operation is then applied to the images, after which, a Cosine window is applied to the image to reduce the frequency effects of the edges of the image when transformed by FT. Lastly, the processed input image is padded using its mean value to the same dimension as the correlation filter. The improved image $s^{'}(x, y)$ is transformed by FT and $kth - Law$ nonlinear filtering to obtain $S^k(u, v)$. The detection process iteratively correlates $S^k(u, v)$ with the stored filters $H(u, v)$ whose dimension is less or equal to the dimension of the input test image. Each correlation output $g(x, y)$ is examined for search peaks with *psr* values greater than or equal to the threshold value τ. The threshold value τ indicates that the object has been located and recognized as an authentic face. If the algorithm proposed in this work detects a face in an iteration, then the coordinates (x, y) and dimension $height, width$ of each detected face is added to a subdetection vector D_{det}. Finally, D_{det} is filtered by the $filterdetections(D_{det})$ function in order to merge detections over a same face region. This is because two filters with nearby dimensions can produce the peak in the same location or nearby locations that include the same portion of the face.

Algorithm 3: Face detection by correlation filters.

Data: Test image $s(x, y)$, detection threshold τ
Result: Vector D_{det} with location and extent of each face detected in $s(x, y)$.

$s'(x, y) \leftarrow preprocessing(s(x, y))$
$S(u, v) \leftarrow \mathcal{F}\{s'(x, y)\}$
$S^k(u, v) \leftarrow |S(u, v)|^k \exp(j\varphi(u, v))$
$D_{det} \leftarrow []$
$count \leftarrow 1$
while $dim\{s(x, y)\} \leq dim\{H_{count}(u, v)\}$ **do**
  $H_{count}(u, v) \leftarrow$ Read the stored filter number $count$
  $g(x, y) \leftarrow \mathcal{F}^{-1}\{S^k(u, v) \cdot H^*_{count}(u, v)\}$
  subdetections $\leftarrow$ searchdetections($g(x, y)$, τ)
  $D_{det} \leftarrow [D_{det}; subdetecciones]$
  $count \leftarrow count + 1$
$D_{det} \leftarrow$ filterdetections(D_{det})

In this section, an algorithm that combines the principles of nonlinear SDF and ASEF correlation filters is proposed. An important feature of this algorithm is that it takes advantage of the facts that the correlation filters are shift-invariant and they allows multiple-object detection with only one operation.

4 Experimental results

In order to design the nonlinear composite correlation filters, the training set T was generated by Algorithm 1 using the Yale B Face database [9]. This database contains 2414 face images of 38 people, each of whom has 60, 63 or 64 gray-scale face images with a resolution of 168×192 pixels and taken under non-uniform illumination conditions. From this set only two face images of person 1 were selected for the initial filter. During the execution of the algorithm, it was observed that face images that are similar to the initial filter produce high psr values, while psr values were low for other facial classes. Whenever psr values are equal to or greater than τ, the test images are included in T. At the output of the Algorithm 1, T contains 1795 facial images.

Two experiments were conducted. In the first experiment, two composite correlation filters were designed in order to locate human faces in two test images. The first filter was designed using the Algorithm 2 with input training set $T =$

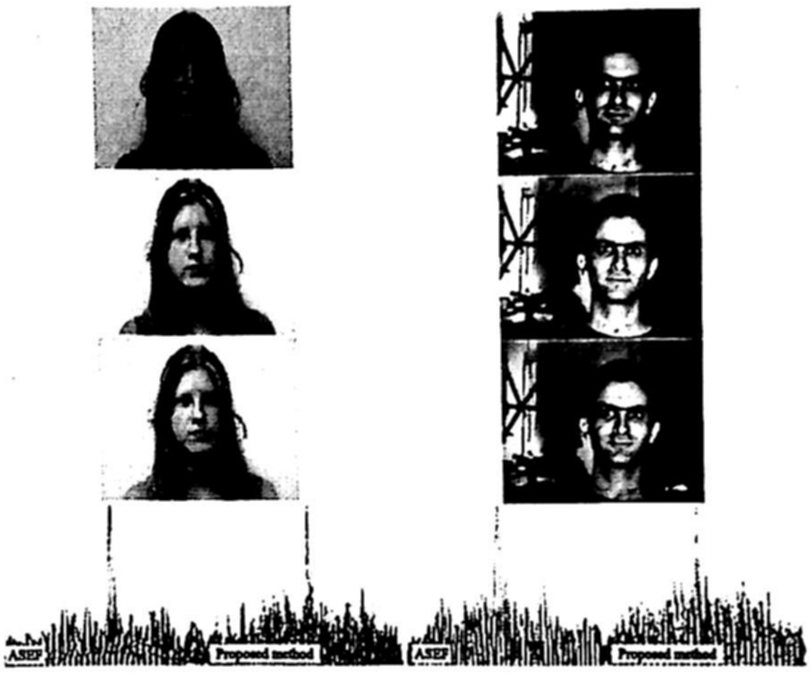

Fig. 1. Correlation output for images with homogeneous and structured backgrounds.

|1795|, so the nonlinear composite correlation filter was designed with 14360 face images. The second filter was designed by the ASEF algorithm using the same input training set $T = |1795|$ as the first filter and applying the image transformations from Table 1. Figure 1 shows the results of this experiment. In the first image, the person appears over a homogeneous background, while in the second image the person appears in a structured background. The second and third rows depict the improvements in illumination while retaining the edge information. The correlation outputs of the filters for each image are shown in the fourth row. As can be seen, the height of the peaks for images with homogeneous background are similar. However, the peak yield with the proposed algorithm is sharper than the peak produced by ASEF in both the homogeneous and structured background.

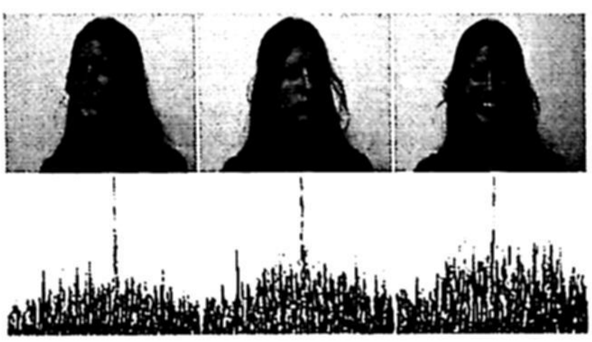

Fig. 2. Correlation output of the proposed strategy when test images contain faces with slight variations in pose and expressions.

The proposed method is able to detect faces that present slight variations in pose as shown in Figure 2. As facial expressions modify the facial structure, a noisy correlation output with a sharp and low peak is produced. In Figure 3, the face in the scene presents non-uniform illumination. In this case, the proposed algorithm responds suitably with a peak in the center of the face region.

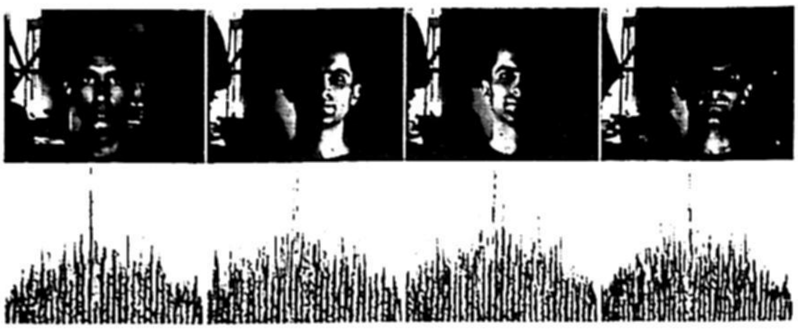

Fig. 3. Correlation output of the proposed strategy when the face contains different conditions of illumination.

Eleven test sets were created in order to perform a more intensive evaluation, and were, in turn, classified into two test sets according to their background. The first set contains images with homogeneous backgrounds from the FEI database [10], and was partitioned into two subsets: 1) Frontal, which consists of 800 scene images with frontal faces, and 2) Pose, which consists of 1000 images where the face is presented in different poses. Figure 4 shows a sample of these sets. The other nine sets contain a total of 576 scene images with a structured background, which correspond to 9 people from the Yale B database [9]. The image set for each person is identified as YaleB11, YaleB22, YaleB27, YaleB28, YaleB29, YaleB30, YaleB32, YaleB33 and YaleB34. Each set contains 64 images taken under non-uniform illumination and presents a pose different from the rest. Figure 5 shows the pose selected for each person. Using the training set T, two banks of filters were created for this evaluation. The first bank contains filters designed by the proposed algorithm, while the second bank contains ASEF filters.

Fig. 4. Sample of Frontal and Pose test sets with homogeneous background.

The performance evaluation was conducted in terms of the following metrics [11]: a) Localization and Recognition Rate LRR, and b) Recognition and Deviated Localization Rate $RDLR$. The LRR metric searches for a value close to

Fig. 5. Sample of pose selected for each person with structured bacground.

100, which indicate good performance, while in *RDLR* an optimum performance is given by a value close to 0. The use of these metrics allow the analysis of any correlation filter's capacity to locate and recognize the target object in scene images. The results of the evaluation are shown in Table 2. As can be observed, the proposed algorithm obtains the best performance, in terms of *LRR* metric, with test sets Frontal, YaleB11, YaleB22 and YaleB32, in which the facial images are frontal or with slight variations in pose. A greater variation in pose causes the algorithm to perform poorly, as shown in the performance achieved with YaleB30 and YaleB333. In terms of this metric, the proposed algorithm outperformed the ASEF algorithm in all test sets. The metric *RDLR* denotes the percentages of images where the filter produced the peak in a location different from the center of the face. In some cases, the detection window captures a face region that could be processed as a partial face. It was noted in the experiments that this is mainly due to non-uniform illumination. An important issue to note in the results obtained with this metric is that the proposed algorithm performs better than the ASEF algorithm in scene images with a structured background, while the ASEF algorithm performed best in those images with homogeneous backgrounds from Frontal and Pose subsets.

Table 2. Performance of the proposed algorithm and ASEF filter in the face detection task.

		Proposed algorithm		ASEF Algorithm	
Background	**Training set**	LRR	RDLR	LRR	RDLR
Homogeneous	**Frontal**	65.5	8.75	62.87	6
	Pose	51.50	20.20	42.80	18.40
Structured	**YaleB11**	53.12	7.80	39.06	4.68
	YaleB22	73.84	7.69	44.61	13.84
	YaleB27	41.53	1.53	9.23	9.23
	YaleB28	46.15	7.69	12.30	33.84
	YaleB29	52.30	15.38	12.30	9.23
	YaleB30	26.15	0.00	12.30	12.30
	YaleB32	92.30	3.07	32.30	36.92
	YaleB33	29.23	3.07	7.69	3.07
	YaleB34	41.53	10.76	9.23	7.69

5 Conclusions

A face detection algorithm based on nonlinear composite correlation filters is presented in this paper. Averaging of training images emphasizes common facial features, which gives a greater robustness to the nonlinear composite correlation filter for detecting face regions in images of real-world scene. The proposed algorithm uses strong classifiers designed with distorted versions of a training set for obtaining tolerance to scale, small variations in rotation and pose, and non-uniform illumination. Topics for future research include the application of optimization techniques for selecting the training images from a face database.

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References

1. Yang, M.H., Kriegman, D.J., Ahuja, N.: Detecting faces in images: a survey. IEEE Transactions on Pattern Analysis and Machine Intelligence **24** (2002) 34–58
2. Z.-Li, S.: 2. In: Face detection. Springer (2005) 13–37
3. Bolme, D.S., Draper, B.A., Beveridge, J.R.: Average of synthetic exact filters. IEEE Conference on Computer Vision and Pattern Recognition (2009) 2105 – 2112
4. Vijaya-Kumar, B.V.K., Mahalanobis, A., Juday, R.: Correlation pattern recognition. Cambridge University Press (2005)
5. VanderLugt, A.: Signal detection by complex spatial filtering. IEEE Transactions on Information Theory **10** (1964) 139–145
6. Casasent, D., Chang, W.T.: Correlation synthetic discriminant functions. Appl. Opt. **25** (1986) 2343–2350
7. Javidi, B., Wang, W., Zhang, G.: Composite fourier-plane nonlinear filter for distortion-invariant pattern recognition. Society of Photo-Optical Instrumentation Engineers **36** (1997) 2690–2696
8. Vu, N.S., Caplier, A.: Illumination-robust face recognition using retina modeling. In: Proceedings of the 16th IEEE international conference on Image processing. ICIP'09, Piscataway, NJ, USA, IEEE Press (2009) 3253–3256
9. Georghiades, A., Belhumeur, P., Kriegman, D.: From few to many: Illumination cone models for face recognition under variable lighting and pose. IEEE Trans. Pattern Anal. Mach. Intelligence **23**(6) (2001) 643–660
10. de Oliveira Junior, L.L., Thomaz, C.E.: Captura e alinhamento de imagens: Um banco de faces brasileiro. Technical report, Department of Electrical Engineering, FEI, Sao Bernardo do Campo, So Paulo, Brazil, (june 2006)
11. Santiago-Ramírez, E., González-Fraga, J.A., Lázaro-Martínez, S.: Face recognition and tracking using unconstrained non-linear correlation filters. Procedia Engineering **35**(0) (2012) 192–201 International Meeting of Electrical Engineering Research 2012.