Multi-Fold Gabor, PCA and ICA Filter Convolution Descriptor for Face Recognition

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Abstract—This paper devises a new means of filter diversification, dubbed multi-fold filter convolution (M-FFC), for face recognition. On the assumption that M-FFC receives single-scale Gabor filters of varying orientations as input, these filters are self-cross convolved by M-fold to instantiate an offspring set. The M-FFC flexibility also permits the self-cross convolution amongst Gabor filters and other filter banks of profoundly dissimilar traits, e.g., principal component analysis (PCA) filters, and independent component analysis (ICA) filters, in our case. A 2-FFC instance therefore yields three offspring sets from: (1) Gabor filters solely, (2) Gabor and PCA filters, and (3) Gabor and ICA filters, to render the learning-free and the learning-based 2-FFC descriptors. To facilitate a sensible Gabor filter selection for M-FFC, the 40 multi-scale, multi-orientation Gabor filters is condensed into 8 elementary filters. In addition to that, an average pooling operator is used to leverage the 2-FFC histogram features, prior to whitening PCA compression. The empirical results substantiate that the 2-FFC descriptors prevail over, or on par with, other face descriptors on both identification and verification tasks.

Index Terms—Gabor filters, PCA filters, ICA filters, filter convolution, face recognition

I. INTRODUCTION

Face recognition, including identification and verification tasks, is highly challenging in practice due to wide intra-class variability in pose and expression, and other disturbances, including illumination, occlusion, misalignment, corruption, just to name a few. An ideal face descriptor, regardless of handcrafted or learning-based, should be invariant to these intra-class difficulties. A plausible remedy is the longstanding filter bank (FB) approaches, where the local structure of overlapping neighborhoods is featured by means of linear local convolutions, or local matches [1], [2]. This is, in general, in line with the renowned deep convolutional neural network (CNN) models [3-5] from the feature extraction perspective. However, the key success factor of the CNNs relies on the availability of large scale training datasets, e.g., DeepFace by Facebook [3] demands a gigantic dataset of 4.4M images with over 4000 identities; DeepID3 [4] by the Chinese University of Hong Kong learns from approximately 300,000 images with 13,000 identities; FaceNet [5] by Google trains CNNs from 200M images spanning over 8M identities.

These prevailing CNN architectures, particularly DeepID3 and FaceNet, reportedly achieve verification accuracies of 99.53% and 99.63%, respectively, on the labeled faces in the wild (LFW) dataset [43], surpassing the human-level performance of 97.53%. On the contrary, the FB approaches, e.g., PCANet [14], discriminant face descriptor (DFD) [15], compact binary face descriptor (CBFD) [16], binarized statistical image features (BSIF) [17], [18], DCTNet [20], etc., are typically equipped with a single or two filtering layers. Despite of being simple and easy of use, these CNN simplifications promise the state of the art robustness to the generic image classification problems including face recognition.

The earliest FB approaches are reviewed and compared in [6]. They share a common three-stage pipeline, referred to as filter-rectify-filter (FRF): (1) a convolutional stage based on the heuristically designed filter banks, e.g., Laws masks, ring and wedge filters, Gabor filters, wavelet transform, packets and frames, discrete cosine transform (DCT), etc.; or other optimal filters, e.g., principal component analysis (PCA) eigenfilters, Karhunen-Loeve transform, prediction error filters, optimized Gabor filters, etc., (2) a nonlinearity, a. k. a. a filter response rectification step, e.g., magnitude, squaring, rectified sigmoid, etc., (3) pooling (filtering) operations, e.g., spatial averaging, smoothing, or nonlinear inhibition, to remove the inhomogeneity in the rectified responses within a homogenous region. The local energy function, includes stage (2) and (3), outputs a set of feature images, one per filter, defining the bases for classification.

In lieu of local energy estimation, Unser [2] summarizes the Nth-order probability density function (PDF) of the filter responses by N histograms. Liu et al. [7], [8] streamlines the Unser’s work by only retaining the first-order PDF, denoted by spectral histogram (SH). This is supported by the statistical ground that, on the independence assumption, the underlying joint probability distribution of the local neighborhoods is characterized by the marginal PDFs, and that the SH is of lower-complexity PDF approximation. The \( \chi^2 \)-statistic, on the other hand, is laid out in [7] as a distance metric comparing two SHs, and the important SH properties are provided in [8].

The data-driven paradigm is first incorporated into the SH techniques in [9] and [10], where a vocabulary of prototype, a. k. a. codebook, is constructed using the unsupervised k-means algorithm. The filter responses are afterward associated to the nearest codeword for the convenience of histogram formation. The emergence of the local binary pattern (LBP) [11] texture operator leads to another distinguished SH variant. Ahonen

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and Pietikäinen [12] equalize the LBP derivation to the FB implementation whereby the LBP is interpreted as a filtering operator based on a set of local derivative filters. The tight connection between the LBP and the FB approaches allows the filter responses to be zero-thresholded and the LBP feature encoding (decimalization) is simulated to denote the extracted features in the SH form. Heikkilä and Pietikäinen [13] observe from the experiments that, under some circumstances, a non-zero threshold might be chosen to stabilize the binary codes.

A. Related Works

In comparison to the FRF model, the contemporary 3-stage SH pipeline, as in [12], is of more parsimonious: (1) a convolutional stage, where the present face recognition works apply Gabor, DCT, or the pre-learned filters, particularly PCA filters, independent component analysis (ICA) filters, and linear discriminant analysis (LDA) filters, (2) a non-linearity, i.e., hashing (binarization) and LBP-like feature encoding, (3) a pooling operation, i.e., histogramming. One of the recent SH techniques is PCANet [14], where the PCA filters are learned from the 2-layer net topology. The experimental results unveil that the PCANet performance remarkably prevails over other state of the arts, including the LDA-learned face descriptors, i.e., DFD [15], and CBFD [16].

In contrast to PCANet, BSIF [17], [18] train the single-layer ICA filter banks from 13 natural images and face regions, such that the statistical independency amongst the ICA responses is maximized. The BSIF performance reported in [18] attests that the block-wise ICA filters stemmed from varying face regions, in conjunction with the Tan and Triggs’s (TT) photometric normalization [19], outperform those learned the pre-selected natural images on the FERET and the LFW datasets. Inspired by PCANet and BSIF, DCTNet is outlined by Ng and Teoh [20]. Despite of being learning-free, the DCTNet performance is shown to be on par with PCANet in the face identification task.

Other relevant face descriptors are Gabor-based approaches, e.g., [23]-[28] (to be detailed in Section II), LBP variants, e.g., [29]-[31], and CNN-motivated architectures, e.g., [32]-[34]. These advancements, together with the FB, SH and CNN approaches discussed in the preceding section, redefine the traditional face recognition problem, shifting from strictly regulatory settings to unconstrained conditions with severe intra-variability, e.g., the LFW images. This evolution has encouraged enormous research efforts, e.g., the pose-invariant face recognition survey in [35], and the pose and expression normalization procedures in [36] and [37].

B. Motivation and Contribution

This work is motivated by the PCANet and BSIF variants, and the recently proposed DCTNet in face recognition. The major shortcoming of the single or 2-layer PCA or ICA filter learning is that it is deficient to abstract the high-level filters like most of the CNN models do. Moreover, it is, in general, susceptible to the training image condition. Imagine if the images are of non-intact, e.g., faces with excessive expression, under or overexposed, partially occluded, or non-frontal with extreme poses; the 2-layer PCANet, as an example, is incapable of rectifying but magnifying such disturbances. The DCTNet performance [20] reveals that the pure mathematical DCT bases seem an ideal alternative for the low-level PCA filters, especially in the pose-oriented cases. Another learning-free option is the biological relevant Gabor filters that are optimally localized in the spatial and frequency domains [22], [23]. To cope with the filter learning constraint of the shallow networks, the multi-fold filter convolution stage is contrived to complementarily fuse the Gabor filters and the pre-learned low-level PCA and ICA filters.

The main contribution of this paper is three-fold: (1) a new means of filter diversification via $\mathcal{M}$-FFC is devised, where the Gabor filters are either self-cross convolved by $\mathcal{M}$-fold, or with other pre-learned PCA and ICA filters to instantiate the offspring sets; (2) the standard Gabor filter bank of 5 scales and 8 orientations in face recognition are recapitulated into the condensed Gabor filter ensemble of 8 elementary filters, abbreviated as $\text{Gabor}_{\text{Std}}$ and $\text{Gabor}_{\text{Cond}}$, respectively, in this paper; (3) the $\mathcal{M}$-FFC histogram features, is leveraged by an average pooling unit to mitigate the dimensionality problem. The $\mathcal{M}$-FFC pipeline, as portrayed in Fig. 1, pursues the simplistic 3-stage SH paradigm in the complex Gabor domain. This signifies that each $\mathcal{M}$-FFC operation yields two offspring sets: one for each real and imaginary constituent, for feature extraction.

This paper builds on our previous work in [58], and offers a
more comprehensive analysis as well as exposition, in terms of $M$-FFC variations. In addition to the learning-free $M$-FFC$_{Gabor}$ descriptor presented earlier (based on Gabor filters), the learning-based $M$-FFC$_{Gabor,PCA}$ and $M$-FFC$_{Gabor,ICA}$ (based on Gabor, PCA and ICA filters), are also explored in this paper. We conduct more extensive experiments to scrutinize the $M$-FFC performance, not limited to face identification, but also the face verification task on the LFW dataset.

The remainder of this paper is organized as follows: Section II underlines the preliminary parts of this work, and Section III elaborates the $M$-FFC pipeline. What follows is the $M$-FFC performance analysis and discussion in Section IV, and the concluding remark is provided in the last section.

II. PRELIMINARY

In this section, Gabor Wavelets and some Gabor-related works in face recognition are reviewed, followed by the PCA and ICA filter learning practiced in our experiments.

A. Gabor Wavelets

Gabor wavelets [21], a filter repository pre-tuned to various spatial frequencies (scales) and orientations, have sparked off much novel research ideas in face recognition. In the spatial domain, the 2D Gabor wavelets in $n$ scales and $u$ orientations are expressed as follows:

$$
\psi_{u,v}(x, y) = \frac{k_{u,v}}{\sigma^2} e^{(-\|k_{u,v} \| z^2/2 \sigma^2)} e^{ik_{u,v}r} = e^{-\frac{\sigma^2}{2}}
$$

where $z = (x, y)$, $\sigma$ denotes the Gabor envelop width, and $k_{u,v} = k_{v}e^{iu \pi / 8}$ refers to the wavelet vector with $k_{v} = k_{\max} / f^v$ and $\theta_{u} = u \pi / 8$. The Gabor-related face recognition works found in the literature typically configure the free parameters as: $u \in \{0, \ldots, 7\}$, $v \in \{0, \ldots, 8\}$, $\sigma = 2 \pi$, $k_{\max} = \pi / 2$, and $f = \sqrt{2}$. Therefore, this parameter setting is termed the de factor standard in this paper, where it derives $\text{Gabor_{std}}$ of 40 multi-scale, multi-orientation filters for each real and imaginary part. The Gabor response of an arbitrary image $I$ is described as the convolution of $I$ and every Gabor filter $\psi_{u,v}$ as follows:

$$
G_{u,v}(z) = I(z) \ast \psi_{u,v}(z)
$$

where $z = (x, y)$, and $\ast$ indicates the convolution operator.

The Gabor-Fisher classifier (GFC) introduced by Liu and Wechsler [23] is one of the earliest Gabor face representation works. In place of SH, the enhanced Fisher linear discriminant (FLD) is applied to the augmented Gabor responses to generate the low-dimensional features. The most well-known Gabor-based SH exemplars are Zhang et al. [24] and Zhang et al. [25]: the former transforms the Gabor magnitude pictures to the local Gabor binary patterns by using the LBP operator, and the latter adopts the local XOR pattern (LXP) operator to manipulate the binarized Gabor responses, before forming the respective histogram features. Xie et al. [26] is an extension to [25], where the block-based FLD is used to compress the Gabor phase and magnitude features. On the other hand, Lei et al. [27] concatenates the histogram features in the spatial, scale and orientation domains, followed by the LDA-based discriminant classification. Similar to [9] and [10], Hussain [28] learns an external codebook to histogram the LBP-like local patterns within large Gabor response neighborhoods.

Most of the existing Gabor-based SH variants necessitates a non-linearity, either LBP, or LXP, to achieve satisfactory performance. To the best of our knowledge, no work is conducted on defining the histogram features directly from the Gabor responses. An exception is the GGPP component presented in [25], where it is aggregated with the histogram features generated by the local XOR patterns as the final descriptors.

B. PCA and ICA Filter Ensemble Learning

Suppose that we are to build the data-driven PCA and ICA filter ensembles from $M$ training images $\{I_{m} \in \mathcal{R}^{h \times h} \}_{m=1}^{M}$. The local pixel-wise patches of size $k \times k$ are identified, and the zero-mean patches are obtained by removing the mean intensity from each patch. A subset of $N$ random patches are later sampled and stacked in columns as follows:

$$
I' = [I'_{1}, I'_{2}, \ldots, I'_{N}] \in \mathcal{R}^{k \times N}
$$

Assuming that we target to learn $i$ PCA filters from $I'$ (to be used in turn to define $i$ ICA filters), the $i$ orthonormal PCA bases $W \in \mathcal{R}^{k \times i}$ are estimated by minimizing the reconstruction error as follows:

$$
\min_{w \in \mathcal{R}^{k \times i}} \|I' - WW^{T}I'\|^{2}, s. t. W^{T}W = I_{i}
$$

The PCA filter ensemble is, thus, furnished with $i$ principal eigenvectors $W_{PCA}$ extracted from the eigensolution of $I'(I')^{T}$ as follows:

$$
W_{PCA} = [w_{PCA,1}, w_{PCA,2}, \ldots, w_{PCA,i}]^{T} \in \mathcal{R}^{i \times k}
$$

where $W_{PCA}$ captures the greatest $i$ variations of $I'$.

Let $W_{ICA} \in \mathcal{R}^{i \times k}$ denotes the ICA filter ensemble to be learned from $I'$ by maximizing the statistical independent of $Z \in \mathcal{R}^{i \times N}$; $W_{ICA}$ is decomposed into two parts:

$$
W_{ICA} = U V
$$

$$
Z = W_{ICA}I' = U V I'
$$

where $U \in \mathcal{R}^{i \times i}$ is an ICA estimation, and $V \in \mathcal{R}^{i \times k}$ is the whitening transformation matrix performing the canonical processing based on $W_{PCA}$. Mathematically, $V$ is defined as follows:

$$
V = D^{-1/2} \cdot W_{PCA}
$$

where $D \in \mathcal{R}^{i \times i}$ stores the sorted $W_{PCA}$ eigenvalues in the main diagonal entries. Assuming also that $V I' \in \mathcal{R}^{i \times N}$ is the dimension-reduced and whitened patches, the orthogonal $U$ is estimated based on the fast ICA algorithm [38] to yield the independent components $Z$. Pursuant to (6), the ICA filter ensemble is filled with $W_{ICA}$ based on $U$ and $V$.

To sum up, the PCA and ICA filter ensemble learning takes 3 primary stages: (1) a set of $N$ mean-removed local patches are sampled from training images; (2) the PCA filter ensemble is obtained from the foremost $i$ principal eigenvectors, and the PCA dimension reduction and whitening are exercised on the
local patches; (3) The ICA filters are estimated with respect to the dimension-reduced and whitened patches.

III. $M$-FFC FACE DESCRIPTOR FORMULATION

In this section, the $M$-FFC pipeline is detailed. It is compared to the most relevant techniques, and the complexity of each step is analyzed.

A. Condensed Gabor Filter Ensemble

The typical Gabor-based SH techniques [24-28] suffer from the curse of dimensionality issue as a consequence of stacking all histogram features for Gabor magnitude or/and phase. In lieu of that, this paper condenses the 40 standard multi-scale, multi-orientation Gabor filters in face recognition, $G_{\text{Bstd}}$, by averaging the Gabor filters of the same orientation across varying scales to define $G_{\text{Cond}}$ as follows:

$$\Phi = \left\{ \varphi_f : \frac{1}{v_{\max}} \sum_{u,v=0}^{u_{\max}-1} \psi_{u,v}, f = u + 1 \right\}_{u=0}^{u_{\max}-1}, \ (9)$$

where $u_{\max}$ and $v_{\max}$ are set to 8 and 5, respectively, in this paper. Fig. 3 shows that the resultant 8 elementary $G_{\text{Cond}}$ filters remain in the initial 8 orientations. Apart from that, the frequency spectrum portrayed in Fig. 2 evidences that, despite of only 8 filters, the $G_{\text{Cond}}$ envelops the entire $G_{\text{Bstd}}$ frequency space. We demonstrate in Section IV (C) that the $G_{\text{Cond}}$ performance is comparable to that of $G_{\text{Bstd}}$, with negligible degradation.

B. $M$-FFC Filter Diversification

For the most basic $M$-FFC instance, let the $G_{\text{Cond}}$ filter set in (9) be the $M$-FFC input, $\{ \varphi_{f_{m}} \in R^k \times k, f_{m} = 1, ..., F_{m}, F_{m} \leq u_{\max} \}_{m=1}^{M}$, these filters are self-cross convolved with another one to render an Gabor offspring set $O_{\text{Gabor}}$ of $L = \prod_{m=1}^{M} F_{m}$ filters as follows:

$$O = \left\{ \sigma_{\ell} \in R^k \times k : \varphi_{f_{1}}^{(1)} * \varphi_{f_{2}}^{(2)} * ... * \varphi_{f_{M}}^{(M)} \right\}_{\ell=1}^{\mathcal{K}} \right\}, \ (10)$$

where $\mathcal{K} = M(k-1) + 1$, $O = \{ O_{\text{Gabor}}, O_{\text{Gabor-PCA}}, O_{\text{Gabor-ICA}} \}$

This implies that, for $M = 2$, $F_{1} = F_{2} = 8$, and $k = 3$, where the two folds are fed with the same eight $G_{\text{Cond}}$ filters of each 3 $\times$ 3, the $O_{\text{Gabor}}$ of $L = 64$ (= 8 $\times$ 8) offspring of each 5 $\times$ 5 (= 2 $\times$ (3 - 1) + 1) is produced as a consequence of the 2-FFC filter diversification; for $M = 3$, $F_{1} = F_{2} = F_{3} = 8$, and $k = 3$, the 3-FFC operation outputs $L = 512$ (= 8 $\times$ 8 $\times$ 8) offspring of each 7 $\times$ 7 (= 3 $\times$ (3 - 1) + 1). To retain the original filter size of $k \times k$, one can simply return the central part of the $M$-FFC output.

Fig. 3 illustrates the 2-FFC filter diversification progression based on the 8 $G_{\text{Cond}}$ filters. For simplicity, the resultant $O_{\text{Gabor}}$ of $L = 64$ offspring is pruned to 36 (= (8 + 1) $\times$ 8/2) unique filters, as the convolution operation is of commutative (applicable to $O_{\text{Gabor}}$ only, due to filter redundancies). We also notice from Fig. 3 that the offspring filters are implanted with distinctive characteristics, e.g., the checkerboard-like filters are obtained by convolving two filters of different directions. The offspring set is thus capable of featuring the salient micro textures consistent to the filter structures, aside from being sensitive to the local edges (just like the ordinary 1-fold Gabor filters). In other words, the offspring serve dual role: edge and texture detectors. This is experimentally examined in Section IV.

The $M$-FFC paradigm is inherently flexible. Apart from the Gabor-Gabor setup, the $M$-FFC flexibility also permits filter convolution amongst $G_{\text{Cond}}$ and other filter banks, e.g., the learning-based PCA and ICA filters, to complement the learning-free $G_{\text{Cond}}$ for the discriminant feature extraction stage. To remain in the complex Gabor domain, for the 2-FFC instance, the pre-learnt PCA and ICA filters are received as the fold-2 input. This derives the Gabor-PCA and Gabor-ICA offspring sets, hereinafter referred to as $O_{\text{Gabor-PCA}}$ and $O_{\text{Gabor-ICA}}$ respectively. The $O_{\text{Gabor-PCA}}$ and $O_{\text{Gabor-ICA}}$ offspring sets are pictorialized in Fig. 4 and 5. The PCA and ICA filter learning steps and the implementation details are respectively given in Section II (B) and IV (B). Note that, the PCA orthonormal and the ICA independent properties are destructed due to 2-FFC. We demonstrate in Section IV (C) that this expense is repaid with a substantial improvement in feature discriminability.

In summary, the $M$-FFC operation produces $L$ offspring for each Gabor real and imaginary constituent. In practice, $M$ is empirically determined for certain degree of performance gain resulted from filter diversification. The $M$-FFC demerit is that $L$ rises exponentially with respect to $M$. This paper, however, only restricts the exploration to 1-FFC and 2-FFC.

C. Convolutional Stage

Given an input image $I \in R^{h \times w}$, and an offspring set $O = \{ \sigma_{\ell} \in R^{k \times k} \}_{\ell=1}^{\mathcal{K}}$, $I$ is convolved with $\sigma_{\ell}$ to yield $L$ responses as follows:

$$G = \{ g_{\ell} : I \ast \sigma_{\ell}, g_{\ell} \in R^{h \times w} \}_{\ell=1}^{\mathcal{K}} \right\}, \ (11)$$

where $I$ is zero-padded by $((K-1)/2$ in advance before the convolution operation to remain the filter response size similar to $I$. If $I$ is represented by columnar zero-mean local patches $I' \in R^{2w \times h}$, (11) is expressed as a linear matrix projection of $O'$ and $I'$:

$$G' = O' I' \right\}, \ (12)$$

where $O' \in R^{\mathcal{K} \times 2w \times h}$ is a matrix stacked with the $L$ offspring in rows, and $G' \in R^{L \times 2w \times h}$ is a composite response matrix to be re-organized into $G$ accordingly.

D. Binarization, Feature Encoding, and Histogramming

The non-linear hashing operator thresholds the $L$ filter responses, refer to $G$ in (11), with respect to 0 to assign a bit ‘1’ to the positive coefficients, and a bit ‘0’ otherwise. In what follows, the binarized filter responses are decimalized into the
$\mathcal{F}_M$-bit integers, ranging from 0 to $2^F_M - 1$, to define $\mathcal{D}(t)$ as follows:

$$\mathcal{D}(t) = \sum_{\mathcal{F}_M=1}^{2^F_M} S\left( \varphi(t \times \mathcal{F}_M - \mathcal{F}_M + \mathcal{F}_M) \right) \cdot 2^F_M - 1,$$

where $T = \prod_{m=1}^{M-1} \mathcal{F}_m$ and $S(\cdot)$ corresponds to the Heaviside step function. Subsequent to that, $\mathcal{D}(t)$ is regionalized into $B$ non-overlapping blocks, unless stated otherwise, where $b = 1, ..., B$. For each $b$ block, the statistical co-occurrences associated to the $2^F_M$ bins, i.e., the block-wise histograms, are aggregated as follows:

$$\mathcal{H}_b(t) = \sum_{x,y} \delta\left( \alpha, \mathcal{D}(t)(x,y) \right), \alpha = 0, ..., 2^F_M - 1,$$

where $\delta(\cdot)$ refers to the Kronecker delta function. The global histogram features to be employed as the $M$-FGFC descriptor is a concatenation of $T \cdot B$ block-wise histograms as follows:

$$\mathcal{H} = [ \mathcal{H}_b^{(t=1)}, ..., \mathcal{H}_b^{(t=T)} ] \in R^{2F_M \cdot B \cdot T}$$

In accordance to the Daugman’s phase-quadrant demodulation code in [25], for the histogram features formulated based on $\mathcal{O}_{\text{Gabor}}$, the composition of $\mathcal{H}_{\text{Re}}$ and $\mathcal{H}_{\text{Im}}$ describes the Gabor phase representation. As the $\mathcal{H}$ definition in (16) unpleasantly doubles the feature dimension, an average histogram pooling operator is introduced in the succeeding section to counter the dimensionality issue.

E. Average Histogram Pooling

$\text{POOL}_{\text{Avg}}$, as the name suggests, is an average pooling unit. It serves an important role of downsampling and regulating the histogram features $\mathcal{H}$ in (16). In another word, it acts as a soft regularizer, in addition to dimension reduction, to uniformize the histogram disparity including burstiness and sparseness. It works as follows to compress the $d$-dimensional $\mathcal{H}$ onto $\mathcal{H'}$ of $d'$ dimensions:

$$\mathcal{H}'_d = \frac{1}{p} \sum_{n=1}^{p} \mathcal{H}_{d-1} \cdot s + n, d = 1, ..., D'$$
where $d = 2^T \times \mathcal{B} \times T \times 2$, $d' = \frac{d-P}{S} + 1$, and $P$ and $S$ describe the pooling window size and the stride step, respectively. In our experiments, $P$ and $S$ are set to 2, by default, to elicit $\mathcal{H}'$ of $2^T \times \mathcal{B} \times T$ dimensions. Subsequent to that, $\mathcal{H}'$ is square-rooted, L2-normalized and WPCA-ed to obtain the compact $\mathcal{M}$-FGFC descriptor.

$F$. Comparison with Relevant Techniques

The deep CNN architectures, in essence, consist of multiple interleaved convolutions, non-linear activations (e.g., absolute or square rectification, rectified linear unit, just to name a few) and $\text{POOL}_{\text{Max}}$ (abbreviation for max pooling), before the last fully connected layer. Due to the reason that the backbone of $\mathcal{M}$-FFC and other relevant techniques, e.g., PCANet [14], BSIF [17], [18], and DCTNet [20], implements the 3-stage SH pipeline, these techniques share some common grounds found in the CNN models. In addition to the convolutional stage, the zero-mean local patch formulation (prior to filter learning and convolutional feature extraction) corresponds to the CNN local contrast normalization. On the other hand, the apparent discrepancy is that these simplified CNN architectures contain no non-linearity, until the hashing and feature encoding stage. Since the $\mathcal{M}$-FFC framework is of single-layer, the non-linear rectification layer is therefore trivial. While PCANet and BSIF only learn a PCA and an ICA filter bank respectively, we learn both PCA and ICA filters for the sake of $\mathcal{M}$-FFC with respect to $\text{Gabor}_{\text{Cond}}$. In contrast, DCTNet only involves the pre-fixed bases, which might be inadequate in the real-world face recognition scenario.

As pointed out in the preceding section, the overly shallow network, either the 2-layer PCANet, or the 1-layer BSIF, restricts the abstracted PCA and ICA filters in the low-level form. To manifest this remark, we exercise PCANet in the 5-layer structure using the FERET-FA images (refer to Section IV (A)). We discern from the PCA filters in Fig. 6 that the 5-layer PCANet learns the negligibly dissimilar low-level filters in each stage. This inspires our thought to merge the omissible multi-layer PCANet topology into a flat single-layer network, as there is no non-linearity in between the convolutional steps. To be more specific, in place of cultivating 16 filters like the 2-layer PCANet configuration, we merely learn 8 layer-1 PCA filters, to be richened via 2-FFC based on the $\text{Gabor}_{\text{Cond}}$. The experimental results in Section IV (D) disclose that the 2-FFC performance is relatively superior to that of PCANet. We also incorporate a dual $\text{POOL}_{\text{Avg}}$ operator, where its role is parallel to $\text{POOL}_{\text{Max}}$ in DeepFace [3], DeepID3 [4], FaceNet [5], and other representative deep CNN architectures. These operators are distinguished from one another in Section IV (C), and the empirical comparisons unveil that $\text{POOL}_{\text{Max}}$ is inappropriate in our case.

![Fig. 5. 2-FFC Gabor-ICA offspring set $O_{\text{Gabor-ICA}}$ derived from $G\text{abor}_{\text{Cond}}$ in fold-1 and ICA filter bank in fold-2.](image)

![Fig. 6. PCA filter banks learned from 5-layer PCANet.](image)
G. Computational Complexity Analysis

Owing to the intense CPU consumption, the convolution operation is practically performed in the frequency domain via the fast Fourier transform (FFT). If \( G_{\text{fGabor}} \) is utilized for the Gabor features of an image, it demands \( \alpha \cdot (6N^2 \cdot \log_2 N^2 + 2N^2) \) real additions, and \( \alpha \cdot (4N^2 \cdot \log_2 N^2 + 4N^2) \) real multiplications, where \( \alpha = u_{\text{max}} \cdot v_{\text{max}} = 8 \times 5 = 40 \). On the one hand, for \( \mathcal{O}_{\text{gabor}} \) with 36 unique offspring, the cost incurred is diminished by \( \alpha = 36 \); on the other, for \( \mathcal{O}_{\text{gabor-PCA}} \) and \( \mathcal{O}_{\text{gabor-ICA}} \), the \( \alpha \) is of 64.

As regard to the single layer PCA filter learning, its time complexity is moderate. The zero-mean patches for \( I' \) in (3) are derived in \( k^2 + k^2 \cdot N \) flops; the covariance matrix of \( I' (I')^T \) requires \( 2 \cdot k^2 \cdot N \) flops; and the eigen-decomposition is of complexity \( O((k^2)^3) \), irrespective to \( N \). Overall, we expense one-half of the PCANet cost to learn \( \mathcal{F}_1 \) filters, equivalent to \( \mathcal{F}_2 \cdot k^2 \) variables.

The time complexity of fast ICA [38] running on \( T \) iterations is reportedly to be of \( O(2 \cdot T \cdot k^2 \cdot (k^2 + 1) \cdot N) \) in [56]. Although the iterative ICA estimation has no close-form solution, the cubic convergence (or at least quadratic) has been proven through the use of non-linear kurtosis contrast function and fixed-point algorithm. The fast ICA algorithm is analyzed thoroughly in terms of accuracy and computational complexity in [57].

The 2-FFC complexity for deriving \( \mathcal{O}_{\text{gabor}}, \mathcal{O}_{\text{gabor-PCA}}, \) and \( \mathcal{O}_{\text{gabor-ICA}} \) is of \( O(\mathcal{F}_1 \cdot \mathcal{F}_2 \cdot k^2 \cdot \mathcal{K}^2), k \neq \mathcal{K} \) (refer to Section III (B)). This is insignificant as \( \mathcal{F}_1, \mathcal{F}_2, k, \) and \( \mathcal{K} \) are typically of small values. If \( \mathcal{O}_{\text{gabor}}, \mathcal{O}_{\text{gabor-PCA}}, \) and \( \mathcal{O}_{\text{gabor-ICA}} \) are computed beforehand, the computational complexity to formulate the 2-FFC descriptor for an image as an image is as follows: the initial patch-mean removal consists of \( \mathcal{K}^2 + \mathcal{K}^2 \cdot h \cdot w \) flops; the single flat convolutional layer costs \( L \cdot \mathcal{K}^2 \cdot h \cdot w \) flops; the hashing and feature encoding stage involves \( 2 \cdot \mathcal{F}_2 \cdot h \cdot w \) flops; and the naive block-wise histogramming progression is of complexity \( O(h \cdot w \cdot B \cdot \mathcal{F}_2 \cdot \log 2) \). On the whole, the most costly part falls on the convolutional layer as \( h \cdot w \gg \max(L, \mathcal{K}, \mathcal{F}_2, B) \). In case of performing filtering in the frequency domain, the complexity is shrank to \( O(L, h \cdot w \cdot \log(h \cdot w)) \). The composite complexity is to be doubled as the 2-FFC descriptor is in the complex Gabor domain.

IV. EXPERIMENTS

For greater clarity, this section emphasizes on three 2-FFC enumerations: the learning-free 2-FFCGabor, and the learning-based 2-FFCGabor-PCA and 2-FFCGabor-ICA, collectively coined 2-FFC descriptors, elicited from \( \mathcal{O}_{\text{gabor}}, \mathcal{O}_{\text{gabor-PCA}}, \) and \( \mathcal{O}_{\text{gabor-ICA}} \), respectively. Each of these offspring sets is defined via 2-FFC with respect to 8 Gabor Cond filters, 8 PCA filters, and 8 ICA filters (see Fig. 3, 4, and 5). There are other two 2-FFC possibilities, i.e., 2-FFCPCA and 2-FFCICA, where the respective 2-FFC offspring sets are derived from the 2-fold PCA and ICA filter convolution stages. However, these descriptors are beyond the coverage of this paper.

The performance of the 2-FFC descriptors is benchmarked on the FERET I (frontal), FERET II (non-frontal), AR, FRGC and LFW datasets in this section. The experimental results are presented in terms of rank-1 identification rate (%) for FERET I, FERET II, AR and FRGC; and area under ROC (AUC) or/and verification accuracy (%) ± standard deviation (ACC±SD) for LFW.

A. Benchmarking Datasets

We consider the following 5 benchmarking face datasets in our experiments:

1) FERET I (frontal) contains a gallery set: FA, with only a single image for each subject (1,196 images in total); and 4 probe sets: FB, FC, DUP I, and DUP II (1,195, 194, 722, and 234 images, respectively), with strictly regulated facial expression, illumination, and time span variations [39]. Each image is re-aligned and cropped into 128 \( \times \) 128 pixels referring to the annotated eye coordinates.

2) FERET II (non-frontal) is composed of 3 frontal reference gallery sets: BA, BJ and BK; and 6 non-frontal probe sets: BC, BD, BE, BF, BG and BH, captured from viewpoint angles of \( \pm 40^\circ, \pm 25^\circ, \pm 15^\circ \) [39]. These repositories are equally furnished with 200 images from the same 200 subjects. As in FERET I, each image is pre-processed into 128 \( \times \) 128 pixels with respect to the eyes and mouth coordinates.

3) AR encloses 2,600 frontal faces provided by 100 subjects in two contact sessions [40]. Each subject contributes 26 images of numerous expressions: neutral, smile, anger, scream; illumination modes: left or/and right lighting on; and occlusions: either sun-glasses or scarf. For each subject, only 2 out of 6 images with neutral expression are on the gallery list, and the remaining 24 images serve as probes. Each image is pre-processed into 165 \( \times \) 120 pixels in our experiments.

4) FRGC includes the 3D scans and high-resolution images, either smile or neutral, snapped under two photometric settings: controlled (in studio with two, or three lighting on), and uncontrolled (at hallway, atria or outdoor with the Vivid 900/910 sensor) [41]. Similar to [42], the uncontrolled FRGC subset is adopted in our experiments, where it repositos images collected from 177 subjects. For each subject, 3 out 5 random images, with 73 \( \times \) 61 pixels each, are selected as galleries.

5) LFW is the only unconstrained face verification dataset in our experiments. It consists of 13,233 images from 5,749 subjects. In place of LFW-a [44], the normalized LFW-HPEN [36] dataset is used in our experiments, where the pose and expression variations are eliminated based on a pre-learned 3D Morphable model. Some exemplars of the original LFW and the LFW-HPEN images are shown in Fig. 7. The 2-FFC performance are examined by using the re-aligned LFW-HPEN images of each 88 \( \times \) 64 pixels, with respect to the 10 splits on the LFW View 2 list. The 6 standard LFW evaluation settings are provided in [45]. This paper, however, only considers the unsupervised and the unrestricted, label-free outside data protocols.

B. Implementation Summary

Prior to the 2-FFC Gabor-PCA and the Gabor-ICA filter diversification stage, a set of 500,000 random patches, with mean-removed, are selected from the gallery images available.
that, the histogram features for each real and imaginary part in accordance to this parameter configuration, the 2-FFCGabor image is regionalized into non-overlapping blocks, except for FRGC and LFW-HPEN. The important reason is that the extreme uncontrolled illumination condition appears on the FRGC images and the undesirable artifacts imposed on the LFW-HPEN images (due to the pose and expression normalization) might confuse the filter learning progression. Therefore, the PCA and ICA filter ensembles for the FRGC and the LFW-HPEN datasets are equipped with the FERET-learned PCA and ICA filters. In our experiments, each PCA and ICA filter ensemble consists of 8 filters.

In a nutshell, to formulate the 2-FFCGabor descriptor, each image is convolved with the 36 unique offspring repositioned in \( \mathcal{O}_{\text{Gabor}} \). The filter responses are zero-thresholded and encoded into 8 feature images denoted by 8-bit integers. Each feature image is regionalized into 8 non-overlapping blocks, unless stated otherwise, and the block-wise histograms are cascaded into 8 histograms, one for each feature image. Subsequent to that, the histogram features for each real and imaginary part are aggregated to define the holistic histogram representation. In accordance to this parameter configuration, the 2-FFCGabor descriptor for an FERET I image, as an example, is of 262,144 dimensions: \((8 \times 8 \text{ blocks}) \times 8^8 \text{ bins} \times 8 \text{ histograms} \times 2\), to be halved onto 131,072 dimensions via the default POOL AVG operator. What follows are the square root and the L2 normalization operations, and the final WPCA compression to obtain the 2-FFCGabor descriptor for performance evaluation by using the nearest neighbor (NN) classifier with Cosine similarity scores.

The derivation procedures for the 2-FFCGabor+PCA and the 2-FFCGabor+ICA descriptors are, in general, equivalent, unless \( \mathcal{O}_{\text{Gabor-PCA}} \) and \( \mathcal{O}_{\text{Gabor-ICA}} \) are adopted in the convolutional stage. The empirical results presented in the following sections are obtained based on the parameters configured in Table I.

### C. Performance Analysis

This section makes use of FERET I as a testbed to assess the GaborCond and POOLAvg performance. The single-fold Gabor, PCA and ICA descriptors, namely, 1-FFCGabor, 1-FFCPCA, and 1-FFCICA, are also explored to unveil the \( M \)-FFC benefit. The experimental results in this section are obtained based on the 1000-dimensional WPCA-compressed features, including the PCANet [14], BSIF [17], BSIFFace [18], and DCTNet [20] descriptors.

#### 1) Performance Analysis on GaborCond

The first-line evaluation is to analyze the GaborCond filter set and compare its performance to that of GaborStd. In this section, 1-FFCGabor and 1-FFCGabor-40 correspond to the 1-FFC descriptors derived based on the 8 GaborCond filters and the 40 GaborStd filters, respectively. While the 1-FFCGabor descriptor is denoted by a single holistic histogram encoding the features conveyed by 8 filter responses, the 1-FFCGabor-40 descriptor is a concatenation of 5 histograms, one for each spatial frequency pre-tuned during the GaborCond construction. The 1-FFCGabor-40 descriptor, in fact, resembles the GGPP representation in [25]. What distinguish the 1-FFCGabor-40 features from GGPP is that the former compresses the demodulated Gabor phase features onto 1000 dimensions using WPCA. The rank-1 identification rates (%) in Table II validate our proposal to replace GaborCond with GaborStd. This is reasoned by the frequency spectrums depicted in Fig. 2.

#### TABLE II

PERFORMANCE SUMMARY FOR 1-FFCGABOR OF 8 FILTERS AND 1-FFCGABOR-40 OF 40 FILTERS, IN TERMS OF RANK-1 IDENTIFICATION RATE (%).

| DESCR. | FB | FC | DUP I | DUP II | MEAN |
|--------|----|----|-------|--------|------|
| 1-FFCGabor-40,7 x 7 | 99.16 | 98.97 | 91.69 | 88.03 | 94.46 |
| 1-FFCGabor-40,9 x 9 | 99.00 | 98.97 | **92.52** | **89.32** | **94.95** |
| 1-FFCGabor,7 x 7 | 99.16 | **99.48** | 91.83 | 86.75 | **94.31** |
| 1-FFCGabor,9 x 9 | **99.25** | 98.97 | 91.41 | 87.61 | **94.31** |

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**Fig. 7.** The original and HPEN-normalized LFW images, where the extreme poses and the excessive expressions are eliminated based on a pre-learned 3D Morphable model.
2) Performance Analysis on \( \text{POOL}_{\text{Avg}} \)

The default \( \text{POOL}_{\text{Avg}} \) operator, with \( P = S = 2 \) as in (17), is investigated. It strides over every two successive histogram elements to averagely halve the full-dimensional 2-FFC\(_{\text{Gabor,Full}}\) features, from 262,144 to 131,072 dimensions. The histogram distribution in Fig. 8 (a) depicts that the 2-FFC\(_{\text{Gabor,Full}}\) features concentrate on some particular bins, leaving with a number of empty bins. This disparity would probably lead to bias in the Cosine similarity score estimation. Fig. 8 (b), on the other hand, discloses that the histogram distribution is regulated and the empty bins are mostly sealed after the \( \text{POOL}_{\text{Avg}} \) operation. This revelation is a strong evidence for why the truncated histogram representation does not seem to undermine the overall performance (refer to Table III).

In addition to \( \text{POOL}_{\text{Avg}} \), the analogous \( \text{POOL}_{\text{Max}} \) operator is probed. We also perceive from Table III that \( \text{POOL}_{\text{Avg}} \) slightly outperforms \( \text{POOL}_{\text{Max}} \). This is due to the reason that, in the CNN architectures, \( \text{POOL}_{\text{Max}} \) is applied to identify the most discriminative responses in consequence of the local matches. The \( \text{POOL}_{\text{Max}} \) employment on the histogram features deforms the original representation. Other informative components, except the maximum one, are discarded owing to dimension reduction.

3) Performance Analysis on 1-FFC and 2-FFC

Besides performance investigation on the 1-FFC and the 2-FFC descriptors, the filter learning practices in [17] and [18] are studied. In our experiments, the natural image-trained ICA filters shared by the BSIF’s authors [17] are re-used; and the block-based ICA filters advocated in BSIF\(_{\text{Face}}\) [18] is explicitly trained for each face region using the FERET-FA images. The key findings perceived from Table IV are:

i) The comparison between the 1-FFC\(_{\text{ICA,7x7}}\) and the BSIF\(_{\text{I7x7}}\) descriptors reveal that the FERET-trained ICA filter bank single out the local neighborhood properties better. The 1-FFC\(_{\text{ICA,7x7}}\) performance, however, is far from satisfactory, as compared to other face descriptors (to be discussed in next section).

ii) The BSIF\(_{\text{Face}}\) block-based ICA filters have been overrated, in comparison to the ordinary holistic ICA filters. This is most probably due to the over-fitting problem, despite the proposed soft assignment (SA) smoothing normalization has also been exercised.

iii) For each of the 2-FFC enumerations, the vanishing of the orthonormal and independent traits of the PCA and ICA filters (due to 2-FFC) is compensated with at least 3% of identification improvement.

Note that, the 1-FFC\(_{\text{PCA}}\) configuration is akin to the 1-layer PCANet architecture, codenamed 1-PCANet in Table IV. The TT pre-processing step [19] is withdrawn from the BSIF and BSIF\(_{\text{Face}}\) pipelines, for a fair comparison.

### Table III

| DESCRIPTOR | FB    | FC    | DUP I  | DUP II | MEAN  |
|------------|-------|-------|--------|--------|-------|
| 2-FFC\(_{\text{Gabor,Full,13x13}}\) | - | 99.33 | 100    | 95.57  | 93.59 |
| 2-FFC\(_{\text{Gabor,13x13}}\) | POOL\(_{\text{Avg}}\) | 99.41 | 100    | 95.98  | 94.02 |
| 2-FFC\(_{\text{Gabor,13x13}}\) | POOL\(_{\text{Max}}\) | 99.33 | 100    | 95.71  | 93.59 |

FIG. 8. Histogram distribution for 2-FFC\(_{\text{Gabor,Full}}\), without POOL\(_{\text{Avg}}\) (a), and 2-FFC\(_{\text{Gabor}}\), with POOL\(_{\text{Avg}}\) (b).
D. Performance Evaluation

This section presents the performance for the 2-FFC\textsubscript{Gabor}, 2-FFC\textsubscript{Gabor-PCA}, and 2-FFC\textsubscript{Gabor-ICA} descriptors with respect to the aforementioned benchmarking datasets.

1) Face Identification: FERET I

The three 2-FFC descriptors are analyzed and compared to the recent face descriptors, in terms of rank-1 identification rate (%), in Table V. On average, the 2-FGFC descriptors prevail over the conventional 1-fold Gabor descriptors: HGPP [25], LGBP + LGXP [26], E-GV-LBP [27] and G-LQP [28]. The merit of the 2-FFC descriptors is that they are directly derived from the 2-FFC offspring sets for each real and imaginary part, without any non-linearity like LBP or LXP. In the meantime, G-LQP histograms the LBP-manipulated local Gabor patterns based on a pre-learned codebook.

PCANet\textsubscript{MP} [14] and PCANet\textsubscript{FERET} [14] are re-implemented using the MultiPIE-learned PCA filter (shared by the PCANet’s authors), and the FERET-learned PCA filters, respectively. Other notable face descriptors, e.g., the learning-based instances, including the LDA-based LBP variants: DFD [15] and CBFD [16] (the convolutional filters are learned from the LBP-like neighborhood properties based on the supervised LDA criterions); the two BSIF derivatives: BSIF [17] (use of the natural image-learned ICA filters) and BSIF\textsubscript{Face} [18] (use of the block-based ICA filters); and the learning-free DCTNet [20] are also selected for performance comparison. Besides of being parsimonious, the data-independent 2-FGFC\textsubscript{Gabor} and DCTNet descriptors are of more discriminative than all other learning-based descriptors, especially on the most challenging DUP I and DUP II probe sets. However, the DCTNet features are regularized via the proposed tied-rank (TR) normalization. The inclusion of the PCA and ICA filters in feature extraction further improves the 2-FFC performance, marking an average rank-1 identification rate of 97.66% for the 2-FFC\textsubscript{Gabor-PCA} descriptor, and 97.62% for the 2-FFC\textsubscript{Gabor-ICA} descriptors. Another finding is that the BSIF descriptors rely on the TT normalization [19]. Their performance drops drastically, from 96.19% to 93.36% (for BSIF\textsubscript{Face}), without TT.

2) Face Identification: FERET II

The 2-FFC descriptors are investigated against pose variation on the FERET II dataset, where the WPCA projection matrix is trained from the frontal gallery images. Table VI discloses that most of the descriptors are sensitive to the awful pose angles of ±40°. To maintain the histogram translation invariant property, a subtle alternation is imposed in our experiments. Rather than non-overlapping blocks, the 2-FFC descriptors are derived from the overlapping blocks such that every block occupies a broader histogramming region. The overlapping ratio is set to 0.5, where a non-overlapping block of $8 \times 8$ (in pixel) is extended to $16 \times 16$, $16 \times 16$ to $32 \times 32$, and the like, with a step size of 8 and 16, respectively. This improves the 2-FFC performance by at least at 2%. We only compare the 2-FFC performance to the re-implemented PCANet and DCTNet descriptors due to the reason that there are limited papers reporting on this dataset. As a whole, the 2-FFC performance surpasses PCANet and DCTNet, as the 2-FFC descriptors are benefited from 2-fold filter diversification and the overlapping trick.

3) Face Identification: AR

The rank-1 identification rates (%) for the PCA-whitened 2-FFC, PCANet and DCTNet descriptors of 180 dimensions are logged in Table VII. The 2-FFC descriptors, on the whole, exhibit remarkable robustness over the PCANet and DCTNet descriptors, particularly to the facial expressions, and the sunglasses and scarf disguises. It is noteworthy to accentuate that we only include 2 frontal faces with neutral expression per subject as the gallery references.

| DESCRIPTOR | F | F | DPU | DPU | MEAN |
|------------|---|---|-----|-----|------|
| HGPP [25]  | 97.5 | 95.9 | 79.5 | 77.80 | 88.58 |
| LGBP + LGXP [26] | 99.00 | 99.00 | 94.00 | 93.00 | 96.25 |
| E-GV-LBP [27] | 98.41 | 98.97 | 81.99 | 81.62 | 90.25 |
| G-LQP [28] | 99.99 | 100 | 93.20 | 91.00 | 96.05 |
| BSIF\textsubscript{Face} [17] | 99.08 | 100 | 93.35 | 92.31 | 96.19 |
| BSIF\textsubscript{Face} [17] | 99.33 | 98.45 | 90.17 | 85.47 | 93.36 |
| PCANet\textsubscript{FERET,1x1} [14] | 99.16 | 100 | 94.04 | 92.31 | 96.38 |
| DFD [15] | 99.40 | 100 | 91.80 | 92.30 | 95.88 |
| CBFD [16] | 99.80 | 100 | 93.50 | 92.20 | 96.63 |
| BSIF\textsubscript{Face,7x7} [18] | 98.41 | 99.48 | 92.38 | 92.31 | 95.65 |
| BSIF\textsubscript{Face,7x7} [18] | 98.16 | 99.48 | 89.75 | 86.75 | 93.54 |
| DCTNet\textsubscript{TR,20} [20] | 99.08 | 100 | 93.35 | 91.45 | 95.97 |
| DCTNet\textsubscript{TR,20} + TR [20] | 99.67 | 100 | 95.57 | 94.02 | 97.32 |
| 2-FFC\textsubscript{Gabor,13x13} | 99.41 | 100 | 95.98 | 94.02 | 97.35 |
| 2-FFC\textsubscript{Gabor,17x17} | 99.41 | 99.48 | 95.57 | 93.59 | 97.01 |
| 2-FFC\textsubscript{Gabor-PCA,13x13} | 99.50 | 100 | 96.26 | 94.87 | 97.66 |
| 2-FFC\textsubscript{Gabor-PCA,17x17} | 99.41 | 100 | 95.43 | 93.59 | 97.11 |
| 2-FFC\textsubscript{Gabor-ICA,13x13} | 99.50 | 100 | 96.12 | 94.87 | 97.62 |
| 2-FFC\textsubscript{Gabor-ICA,17x17} | 99.33 | 100 | 95.17 | 93.59 | 97.16 |
Based on the probably under or overexposed images.

The downside of the DFD FFC descriptors are relatively immune to the extreme uncontrolled illumination condition. The DFD performance is assessed on the uncontrolled FRGC subset, and DCTNet descriptors. Table VII discloses that the 2-FFC PCANet (the PCA filters are learned from the FRGC gallery set), and DCTNet descriptors. The 2-FFC performance is positioned in the second place, after MRF-Fusion-CSKDA [48]. Unlike the single-type 2-FFC descriptors, the MRF-Fusion-CSKDA descriptor is of multi-type cascading multi-scale LBP, multi-scale local phase quantization (LPQ), and multi-scale BSIF features. Instead of the most naive NN classifier, the MRF-Fusion-CSKDA [48] descriptor is the Spartans [49] descriptor is the latest one on the LFW official list. In place of one-to-one matching like our case, it synthesizes a number of new faces under a wide range of 3D rotations based on a 3D generic elastic model to yield discriminative matching scores. However, the Spartans performance is capped at 0.9428, marginally below the proposed 2-FFC descriptors.

4) Face Identification: FRGC

To recap, for FRGC images with uncontrolled illumination, the FERET-learned PCA and ICA filters are used to define the 2-FFCGabor-PCA and 2-FFCGabor-ICA descriptors. The 2-FFC performance is assessed on the uncontrolled FRGC subset, and is compared to the DFD (based on the results reported in [42], PCANet (the PCA filters are learned from the FRGC gallery set), and DCTNet. Table VIII discloses that the 2-FFC descriptors are relatively immune to the extreme uncontrolled illumination condition. The downside of the DFD and PCANet descriptors is that the LDA and PCA filters are trained based on the probably under or overexposed images.
The ROC for the 2-FFC descriptors and the most recent LFW-listed descriptors are portrayed in Fig. 9. Note that, the TPR and FPR for MRF-Fusion-CSKDA are not provided.

The second experiment assesses the 2-FFC performance on the LFW unrestricted, label-free outside data protocol. Since the class label information is made known in this setting, the joint Bayesian (JB) [50] is practiced for supervised subspace learning, without any external images. This restriction forces us to compress the 2-FFC descriptors to 500 dimensions using WPCA [51]. The flip-free strategy elaborated in [54] is also implemented, such that the similarity scores are estimated by averaging the four possible combinations stemmed from the original and the horizontally flipped images. Lastly, the 2-FFC performance is probed by replacing the NN with the linear SVM classifier. In accordance with Table X, our observations are as follows:

i) The 2-FFC performance is comparable to that of 3-layer hybrid ConvNet-RBM network [34]. However, as appose to the ConvNet-RBM architecture, the 2-FFC pipeline is of far more simplistic. For example, the ConvNet-RBM network represents a single input image with 12 color and grayscale face regions; each pair of a region is expanded to 8 modes to extract the local relational visual features. The hybrid ConvNet-RBM network [34] is a single input image with 12 color and grayscale face regions; each pair of a region is expanded to 8 modes to extract the local relational visual features. However, as appose to the ConvNet-RBM architecture, the 2-FFC pipeline is of far more simplistic. For example, the ConvNet-RBM network represents a single input image with 12 color and grayscale face regions; each pair of a region is expanded to 8 modes to extract the local relational visual features.

ii) The MLBPH + MLPQH + MBSIFH [52] and CBFD [16] descriptors are multi-scale and multi-type: similar to [48],
the former is a combination of multi-scale LBP, LPQ, and BSIF (either in 4 or 5 scales); whereas the latter stacks the CBFD descriptors (defined from 3 input representations) with another 5 descriptors, including LBP, etc. The 2-FFC descriptors are disclosed to be parallel to each individual MLBPH, MLPQH and MBSIFH. Furthermore, the 2-FFC descriptors are of more discriminative as compared to the single-input, single-type CBFD descriptors.

The multi-scale HD-LBP [51], HPEN + HD-LBP [36], and HPEN + HD-Gabor [36] descriptors are derived from the dense fiducial landmarks detected by using Cao et al. [55]. The MDML-DCPs [31] descriptor is of multi-input, where its final performance is measured on a fusion score of 9 feature representations of a single image, including 2 holistic and 7 local landmark features.

Another interesting observation is that most of the non-CNN descriptors, including the 2-FFC descriptors, defeat the LFW-trained deep CNN, i.e., MatConvNet + JB [53], where its overall performance is obtained from the best-performing 16 networks, out of 30 (an image is separated into 5 face regions with 6 scales). This attests that a deep-network would fail to perform as it is, if the training data is insufficient.

To conclude, the existing face descriptors are leveraged by taking multiple representations of a single image for feature extraction, either in multiple scales, or/and in multiple regions. Besides, the multi-type descriptors such as [16] and [52] do not reflect the actual performance. It is therefore unreasonable to compare their performances to the single-type, single-input descriptor like the proposed 2-FFC descriptors. For the sake of performance gain, it is possible to stack the 2-FFC descriptors with features extracted from different image representations, or/and other heterogeneous descriptors.

V. CONCLUSION

This paper outlines a new means of filter diversification, where Gabor, PCA and ICA filters are cross convolved by $M$-folds to instantiate offspring filter sets for feature extraction. We reveal through extensive experiments that it is practically viable to condense the 40 multi-scale, multi-orientation Gabor filters in most of the face recognition works into only 8 filters. The average histogram pooling operator, on the contrary, is proven to be indispensable in two important roles: dimension reduction, and soft histogram regularization. We evidence that the proposed 2-FFC descriptors are superior to other influential face descriptors on five face identification datasets, i.e., FERET I (frontal), FERET II (non-frontal), AR, and FRGC. The experimental results also substantiate that the single-type, single input 2-FFC descriptors achieve the state of the art verification standard scrutinized on the LFW dataset. For future work, the 2-FFC performance on the LFW dataset will further be explored by taking multi-scale, or multi-input image representations. The downside of $M$-FFC will also be remedied to bound the offspring set to a reasonable size for $M > 2$.  

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