WAVELET PACKET CORRELATION METHODS IN BIOMETRICS

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ABSTRACT

We introduce wavelet packet correlation filter classifiers. Correlation filters are traditionally designed in the image domain by minimizing some criterion function of the image training set. Instead we perform classification in wavelet spaces that have training set representations which provide better solutions to the optimization problem in the filter design. We propose a pruning algorithm to find these wavelet spaces using a correlation energy cost function, and we describe a match score fusion algorithm for applying the filters trained across the packet tree. The proposed classification algorithm is suitable for any object recognition task. We present results by implementing a biometric recognition system using the NIST 24 fingerprint database, and show that applying correlation filters in the wavelet domain results in considerable improvement of the standard correlation filter algorithm.

1. INTRODUCTION

The theory of advanced correlation filters has evolved from the literature of optical pattern recognition in the last two decades [1]; they have proved effective classifiers in a number of applications, among them biometric recognition and automatic target recognition [2].

Correlation filter designs use the image intensity domain of training examples to compute a class template that produces characteristic correlation outputs to distinguish between authentic users and impostors. When applying the filter for testing the authenticity of a new target image, the output plane is expected to have a shape containing a correlation peak if the image is authentic, but no such peak if the image belongs to another class. Properties of correlation filter classifiers include graceful degradation, shift invariance and closed-form solutions [1].

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Advanced correlation filter designs control properties of the training output planes, by solving optimization functions related to quantities such as peak sharpness or noise tolerance [3]. The effectiveness of correlation filter design relies on the structural and geometric characteristics of the images available for training; the collection of examples must be representative of expected within-class variations. In this work, we aim to find better design spaces in the sense of the optimization problem of correlation filters. We present an algorithm that finds a specific wavelet packet decomposition of the training images where the image's wavelet coefficients allow a better solution to the optimization problem posed.

In the case of correlation filter classifiers, we have specific interest in the wavelet packet trees where the average output plane of its leaf subspaces yields the smallest amount of energy possible for the decompositions of the images in the training set. We refer to the set of correlation filters designed in this tree structure as wavelet packet correlation filters. We propose a pruning algorithm to find these wavelet spaces, and a fusion method for combining the subspace match scores in the testing stage. In addition, since wavelet transforms are not shift invariant, we present a method for computing match scores approximately invariant to target image shifts.

The rest of this paper is organized as follows. Section 2 describes correlation filter classifiers, and Section 3 presents the proposed classification algorithm. We explain the experiment specifications and results in Section 4, and Section 5 gives conclusions.

2. CORRELATION FILTER RECOGNITION

A correlation filter is designed specifically for the recognition of one pattern class, represented by a set of training images. Applying the filter to any image produces a correlation plane output, which measures the correlation between the image and translated versions of the (space-reversed) filter. The objective is to build a filter which outputs strong correlation peaks when applied to any authentic image (i.e.,

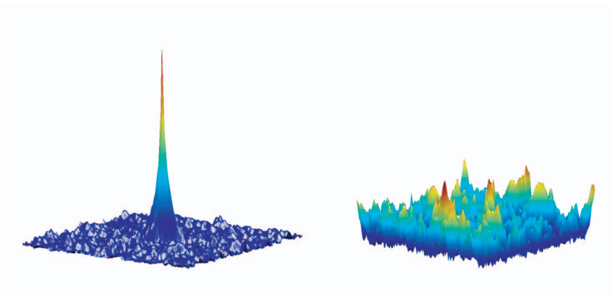


Fig. 1. Left: an authentic correlation plane output. Right: an imposter correlation plane output.

containing the filter's pattern class). To achieve this, correlation filters are designed to produce a peak for all authentic training images, with the expectation that this response will generalize to the entire class of authentic images.

We label the response of a correlation filter to an image as correlation plane $\mathbf{C}$. Figure 1 shows typical values for $\mathbf{C}$ when there exists a match, and when there exists no match. To obtain a match metric, the presence of a sharp peak in $\mathbf{C}$ must be quantified. To do this, we use the peak-to-correlation energy (PCE) metric, defined as

$$PCE(\mathbf{C}) = \frac{max(|\mathbf{C}|) - mean(|\mathbf{C}|)}{std.dev.(|\mathbf{C}|)}. \tag{1}$$

The PCE match metric, like the filtering operation, is shift-invariant. Therefore, correlation filter recognition is invariant to translations of the input image. Note that we do filtering in the Fourier domain.

Filter Design. Let $\mathbf{h}$ be the correlation filter values, formed by appending all columns of the transfer function into one vector. Let $\mathbf{x}_i$ represent the transform of the ith training image, vectorized in the same way. Then filter $\mathbf{h}$ is designed as some function of matrix $\mathbf{X}$, where the columns of $\mathbf{X}$ hold the training images, i.e. $\mathbf{X} = [\mathbf{x}_1 \cdots \mathbf{x}_i \cdots \mathbf{x}_N]$.

The simplest filter design is a linear combination of the training images, $\mathbf{h} = \mathbf{X}\mathbf{w}$, where the weight vector $\mathbf{w}$ is calculated as some function of the training data. Although it may be intuitive to build a filter template as a weighted average of the training images, the recognition performance of such filters is less than optimal [3][4]. Since good discrimination depends on the sharpness of the correlation peaks, more advanced filter designs address this problem directly.

MACE Filter. The Minimum Average Correlation Energy (MACE) filter design suppresses the sidelobes of the correlation planes by minimizing their energy. First, we assume the training images are centered and constrain the origin of their correlation planes to have value 1; these will be the correlation peaks. Subject to this constraint, we wish to minimize the average energy E of the correlation planes. Let $\mathbf{D}$ be a diagonal matrix that carries the average power spectrum of the training images on its diagonal. Then given a filter $\mathbf{h}$, E may be expressed as the quadratic term $E = \mathbf{h}^{+}\mathbf{D}\mathbf{h}$, where $^{+}$ denotes conjugate transpose. This constrained minimization problem has a closed-form solution, yielding the MACE filter design

$$\mathbf{h} = \mathbf{D}^{-1}\mathbf{X}(\mathbf{X}^{+}\mathbf{D}^{-1}\mathbf{X})^{-1}\mathbf{u}, \tag{2}$$

with vector $\mathbf{u}$ containing the peak constraints (a vector of ones). Note that lower values for correlation energy E are related to sharper peaks and better discrimination. We will extend our optimization of this term in the following section. The correlation filter design which we implement for testing is the Optimal Trade-off Synthetic Discriminant Function (OTSDF) filter [3]. This may be considered a generalization of the MACE filter, which allows us to adjust for noise tolerance.

3. WAVELET SUBSPACE FILTERS

Wavelet packet analysis provides a family of wavelet representations using an iterative filter bank algorithm [5]. Specifically, given an orthogonal low-pass filter g, and its complementary high-pass filter h, both of finite support, the single-level expansion of a signal $x^{(i)}$ at level i is given by

$$x^{(i)}[n] = \sum_{k\in Z} x_g^{(i+1)}[k]g[n-2k] + \sum_{k\in Z} x_h^{(i+1)}[k]h[n-2k], \tag{3}$$

where

$$x_g^{(i+1)}[n] = \sum_{k\in Z} x^{(i)}[k]g[k-2n], \tag{4}$$

and similarly for x_h. Superscripts indicate the level of decomposition signals belong to, and subscripts if a signal is generated through the low-pass channel g or the high-pass channel h. For separable wavelets, this operation is performed along the rows of the image, and the resulting low-pass and high-pass images undergo the same process operating along their columns, producing four decomposition signals denoted by x_{gg}, x_{gh}, x_{hg} and x_{hh}. A wavelet packet transform iterates this process for a given tree structure.

Correlation filters are typically designed and applied in the image intensity domain. However, we may extend correlation filter recognition to any domain that maintains a consistent spatial relationship, such as a wavelet subband. This may improve filter performance, if the features contained in wavelet subspaces better facilitate discrimination between authentic and imposter images.

We propose to select the optimal wavelet subspaces in which to design and apply correlation filters using wavelet packets to define our subspace options. Let $\tilde{\mathbf{X}}$ represent the training images after projecting them into a particular wavelet subspace; as before, the columns of $\tilde{\mathbf{X}}$ are composed of the vectorized image spectrums. To select the useful subspaces, we need a way to measure the fitness of the

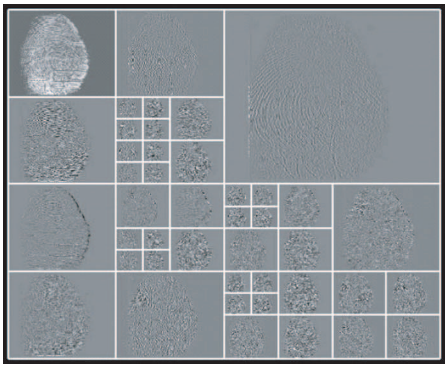


Fig. 2. Wavelet packet decomposition for a sample image class, after pruning for correlation filter fitness.

Fig. 3. Sample images from one fingerprint class.

subspace data $\tilde{\mathbf{X}}$ for correlation filter recognition. To do this, we use the minimum possible correlation energy we can achieve in this subspace, computed by substituting (2) into $E = \mathbf{h}^{+}\mathbf{D}\mathbf{h}$. For transformed images $\tilde{\mathbf{X}}$, the minimized energy $\tilde{E}$ simplifies to

$$\tilde{E} = \mathbf{u}^T(\tilde{\mathbf{X}}^{+}\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{X}})^{-1}\mathbf{u}. \tag{5}$$

Now we can further optimize our correlation planes, by finding transformations that yield lower values for $\tilde{E}$. We define our fitness metric F as

$$F = 1/\tilde{E} \tag{6}$$

so that higher fitness scores correspond to better expected filter performance. Conceptually, this metric tells us how sharp we can make the correlation peaks for our training images in this subspace. For more details, see [6].

Wavelet Packet Pruning. We select a wavelet packet tree for each image class by pruning the full tree according to the fitness metric (6). First, we choose a wavelet type and fully decompose the training images (although we restrict the number of levels of the decomposition tree). Then we prune the tree from the bottom up, using the following rule: If V_0 represents a parent space to four child subspaces V_1, W_1, W_2, W_3, evaluate the inequality

$$F(V_0) > F(V_1) + F(W_1) + F(W_2) + F(W_3), \tag{7}$$

where operator $F(\cdot)$ computes the fitness metric of the space. Here V_1, W_1, W_2, W_3 are the spaces of signals $x_{gg}^{(i+1)}$, $x_{gh}^{(i+1)}$, $x_{hg}^{(i+1)}$ and $x_{hh}^{(i+1)}$, respectively. If the inequality holds, we select the parent space instead of the child spaces; if not, we select the child spaces and represent their collective fitness score as the sum of individual scores. (We use the sum of scores because the fitness metric is a linear function of subspace size and wavelet packets are orthonormal). At the end of the pruning process, we are left with a tree of wavelet spaces that are most useful for the recognition of the pattern class represented by the training images. Figure 2 shows an example of a packet decomposition resulting from this algorithm. In each of these subspaces, we use the transformed training data to build an OTSDF correlation filter. Once we have stored the wavelet packet tree structure and the subspace filters, we are finished with the training process for this class.

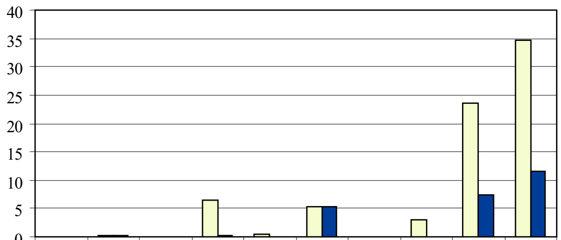
Shift-Invariance. To apply subspace correlation filters to an image, we must first decompose the image according to the correct wavelet packet tree. Then we may apply each of the subspace filters, and compute PCE match scores for each. These scores are summed to obtain the final match score. However, wavelet decomposition is not a shift-invariant operation, because of the downsampling involved. A shift in the original image will only periodically correspond to a shift in the wavelet subspaces. As a result, the performance of subspace correlation filters is no longer shift-invariant; instead, it peaks and decreases periodically as the input image is shifted.

To solve this problem, we design one further correlation filter in the original image domain. This filter is applied to the image first in order to align it; i.e., we observe the location of the correlation peak in the output and correct for any translation. Then we continue with the decomposition and the use of subspace filters, which allow for superior discrimination. This technique restores shift invariance without adding to the computational complexity.

4. RESULTS

For testing, we used a subset of the NIST 24 fingerprint dataset [7]. We used 10 classes, each containing 100 images of a rolling fingerprint. The images are often challenging because of the deformations and partial prints that result from the rolling finger movement. Figure 3 shows sample images from one fingerprint class.

Fingerprint recognition can be accomplished with zero or very near zero error using standard correlation filter recognition, if the training set is large enough. Here, we limited our training set size to 5 authentic images along with 7 imposter images, making the task more difficult. Our reason for restricting the available training data is to demonstrate



	1	2	3	4	5	6	7	8	9	10
CF	0	0.23	0	6.55	0.41	5.20	0	3.10	23.63	34.68
WPCF	0	0.23	0	0.23	0.06	5.20	0	0	7.31	11.52

Fig. 4. EERs for every class for the standard correlation filters and the wavelet packet correlation filter classifier.

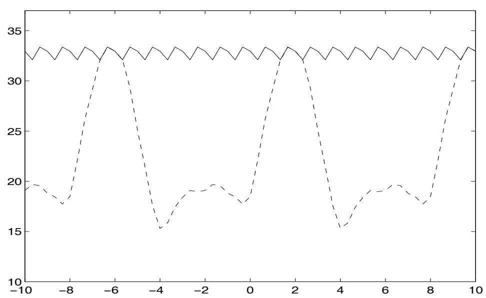


Fig. 5. PCE values for a range of possible horizontal shifts for a sample authentic image. A continuous line is used for the WPCF with pre-filtering, and a dashed line for the WPCF without pre-filtering.

the improvement offered by the proposed algorithm in difficult conditions.

We compared the standard correlation filter algorithm, using OTSDF filters, to the proposed WPCF algorithm (also using OTSDF filters in the wavelet subspaces). For our wavelet packet decompositions, we experimented with the Daubechies family of wavelets and selected the length-2 wavelet, equivalent to Haar, for the decompositions.

For each fingerprint class, we sequestered an arbitrarily chosen training set of images to train both types of classifiers. Then we applied the classifiers to all other images from that class to generate authentic scores, as well as the remaining images from the data set to generate imposter scores. We chose a score threshold for recognition which gave equivalent rates of false acceptance and false rejection, and recorded this error as the Equal Error Rate (EER) for that image classifier. The results are displayed in Figure 4.

The proposed WPCF algorithm performs better than the standard correlation filter, decreasing error in most image classes where improvement is possible. Average EER across all classes improves from 7.38 to 2.46; the difference is especially noticeable for classes 9 and 10, which exhibit markedly high levels of noise and deformation.

To demonstrate the approximate shift invariance of our proposed algorithm, we selected a sample test image from class 8 and shifted it horizontally across a range of 20 pixels (including interpolated sub-pixel shifts). We applied the WPCF algorithm with and without using pre-filtering for alignment, and the resulting match scores are plotted in Figure 5; shift-invariance is restored by using pre-filtering.

5. CONCLUSIONS

We proposed to extend the optimization of correlation filter design to wavelet packet subspaces, where they may be applied while still performing valid cross-correlations (in separate frequency subbands). We may think of the subspace coefficients as texture features, which may represent more consistent or more discriminatory features for our image classes; as a result, the optimization can be more successful. Comparing the proposed wavelet packet filters to standard filters, we see a significant improvement in accuracy, especially for difficult recognition problems. In addition, we do not have to sacrifice shift-invariance as long as we pre-filter in the image domain for alignment.

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