FINGERPRINT IMAGE ENHANCEMENT USING A BINARY ANGULAR REPRESENTATION

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ABSTRACT

In this paper, we explore a novel approach to enhancing fingerprint images using a new binary directional filter bank (DFB). Automated fingerprint identification systems (AFIS) are used to classify a fingerprint in a large volume of images. Many approaches to AFIS have been suggested, most sharing in common the idea of extracting discriminate feature representations. As part of that process, the raw fingerprints are often smoothed, converted to binary and thinned.

Conventional directional methods, which have been used successfully in the past, provide representations that delineate the directional components in the fingerprint image enabling separation, and enhancement. Our binary DFB receives a binary input and outputs a binary image set comprised of directional components. Through proper weighting and manipulation of the subbands, specific features within the fingerprint can be enhanced. We propose a new enhancement approach that remains in the binary domain for the entire process. This paper provides a description of a new binary DFB and its application to fingerprint pre-processing.

1. INTRODUCTION

Fingerprint identification is a biometric technology that requires great accuracy and high efficiency to operate on a vast amount of images. An automatic fingerprint identification system consists of four general steps: acquisition of the fingerprint, representation of that fingerprint, feature extraction, and fingerprint identification or classification [1]. Many approaches to classification have been proposed in the literature. The approaches are varied in the stages of classification that occur. Some use higher level features, such as directional elements [2], or use predefined classes [3] to recognize fingerprints of different classes. Others use local features, such as ridge line shapes, bifurcations, and ridge endings [4], or rely on feature measurements (ridge angles, separation, and curvature) [5] to determine the various classes. Often control over acquisition is limited because of problems in acquisition techniques. The ability to identify many feature details is dependent on the quality of the fingerprint that has been acquired. Thus, it is often necessary to pre-process the fingerprint to improve the clarity of the feature details so they may be properly represented in preparation for classification.

A number of techniques have been proposed to improve minutiae features in fingerprints [6] [7] [8] [9]. Typically these algorithms rely on arithmetic performed with floating point precision and, as a final step, convert the image to binary form prior to feature extraction.

In this paper, we consider a novel approach to fingerprint enhancement using filter banks that operate in a binary finite field–that is, they perform the equivalent of convolution and filtering in the binary domain, a.k.a. GF(2). As a recent historical note, the notion of employing finite field arithmetic for conventional filter bank implementation was originally introduced in [10] and later developed in [11]. Extensions to other forms of filter banks are not possible by direct extension thus, an important part of this development is the introduction of a directional filter bank for binary images, where the output images represent directional feature components of the input, equivalent to fan filter outputs. Such a decomposition can be used for feature extraction, classification, and enhancement. For enhancement of fingerprints, the directional components provide the ability to separate important ridge characteristics from undesirable discontinuities. Once the image is decomposed, the undesirable features can be suppressed in the subband reconstruction, leading to an enhanced image that is better suited to feature extraction

In the sections that follow, we will develop the theory of finite field filter banks, discuss the new angular filter bank, and then show an example of its application to the enhancement of a fingerprint.

2. FINITE FIELD FILTER BANKS

The classical analysis/synthesis two-band filter bank, a block diagram of which is shown in Figure 1, is a critically sampled linear time varying system. An input signal is decomposed using a lowpass analysis filter, $H_0(z)$, and a highpass analysis filter, $H_1(z)$. Reconstruction occurs in the synthesis section using a lowpass filter, $G_0(z)$, and a highpass filter, $G_1(z)$. If the filters are chosen correctly, we can obtain perfect reconstruction, i.e. $X(z) = z^{-n_0}X(z)$ where n_0 is an integer delay.

Finite field filter banks are similar to the classical system but with the added constraint that the analysis output representation is constrained to a predetermined number of

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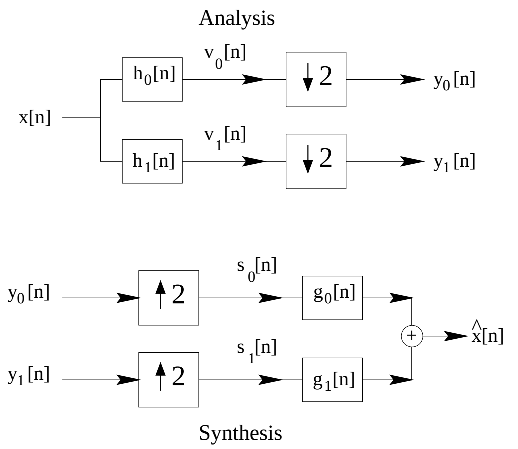


Figure 1: Two-band analysis-synthesis filter bank.

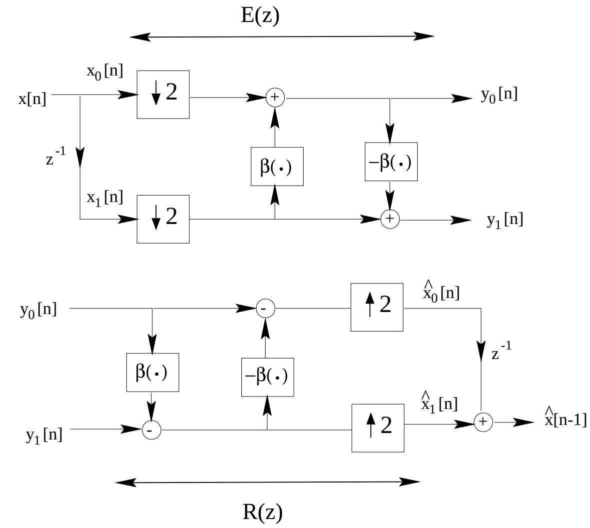


Figure 2: Two-band analysis-synthesis filter bank using a ladder implementation.

finite levels. Originally introduced by Vaidyanathan [10], this idea is motivated by an interest in constraining the dynamic range expansion.

The finite field filter bank is a simple extension of the classical system where arithmetic operations are performed modulo-N [10]. To reconstruct, filtering in the synthesis portion is performed using the same modulo-N arithmetic and the bands are combined using modulo-N addition. This alone does not guarantee a result that matches the input. However, a mapping based on the filter gain, M, and the dynamic range, N, can achieve exact reconstruction. The output $\widehat{x}$ will be an exact reconstruction of the input image x provided two conditions are met. First, the modulo operation field size must be greater than or equal to the field size of the input, N'. This is required to avoid information loss. Second, a constraint is placed on the gain of the system, M. Let us assume the filter coefficients are integers. The gain is dependent on the system filters, that is

$$M = (\sum_n |h_0[n]| \times \sum_n |g_0[n]|) + (\sum_n |h_1[n]| \times \sum_n |g_1[n]|),$$

where $h_0[n]$ and $h_1[n]$ are the analysis filters and $g_0[n]$ and $g_1[n]$ are the synthesis filters. A crucial relationship is necessary to obtain perfect reconstruction. M and N are required to be relatively prime, i.e. they must have no common factors.

While the finite field property of the subband outputs might appear highly attractive, the appearance of the resulting subbands can be very noisey, owing to an implicit scrambling of amplitude values. The degree this "value" scrambling occurs is dependent on two variables, the system gain M and the output field size N. Generally speaking, the larger the value of N (with respect to M) the less severe the wrap-around effects. However, even for $N = 255$ and modest values of M, wrap-around arithmetic can still introduce a noisy scrambled appearance to the output. Depending on the system gain, the original image can be quite difficult to recognize because, it essentially wraps around itself several times. This issue must be handled in some way in order for the finite field filter banks to be useful. In spite of this inherent difficulty it is interesting to observe that the new binary directional filter banks, which we introduce next produce well-balanced filtered representations.

3. DIRECTIONAL DECOMPOSITION

In this section, we will define a 1-D filter bank structure that can be extended to 2-D. We will then show how this 2-D structure can be modified to perform all of its operations in a binary field, GF(2). As in [13], we begin with a lowpass filter representation that is a halfband filter. The equivalent lowpass filter can be expressed as

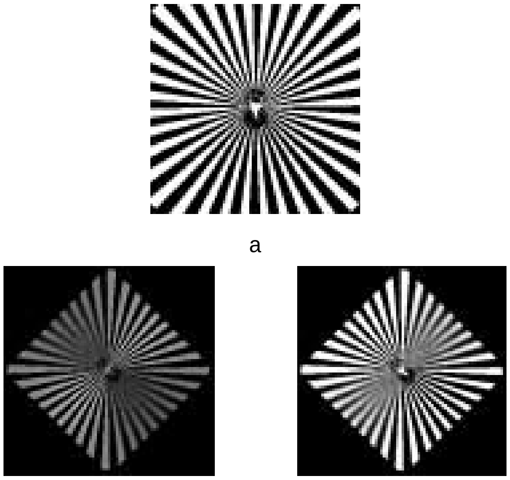
$$H_0(z) = \frac{(z^{-2N} + z^{-1}\beta(z^2))}{2}.$$

Similarly, the highpass filter is expressed as

$$H_1(z) = -\beta(z^2)H_0(z) + z^{-4N-1}.$$

Implementation of these filters can make use of a generalized polyphase filter structure shown in Figure 2. Ansari [13] shows that this system can be extended into a 2-D system by replacing the transfer function $\beta(z)$ with $\beta(z_0)\beta(z_1)$, the delays z^{-1} with 2-D delays $z_0^{-1}z_1^{-1}$, and the downsampler with a downsampling matrix.

The first stage of a directional filter bank is commonly a fan filter, formed by modulating a diamond filter and using a downsampling matrix, $M = [\begin{smallmatrix} 1 & 1 \\ 1 & -1 \end{smallmatrix}]$. The fan filter characteristic can be achieved by modulating either the input image or migrating it to the diamond filter. Modulation does not translate clearly to binary fields, however, which presents a challenge. We circumvent this problem by converting all z_0 to $-z_0$ in $H_0(z_0, z_1)$ and $H_1(z_0, z_1)$ resulting in a bi-directional filter bank with a grayscale outputs. As an example, we filter the test image shown in figure 3(a). The images shown in Figure 3(b) and 3(c), depict the grayscale outputs of the filter bank.



a

b c

Figure 3: Test image for directional filter bank is shown in (a). Two-band grayscale decomposition shown in (b) and (c).

Ultimately, we desire a binary filter bank where a binary input results in a binary output. Assume, rather than conventional filters, we have integer halfband filters with $\frac{\pi}{2}$ cutoff frequencies. If we perform all operations modulo-2, the output would be binary but with an undesirable noisy appearance. However, with this proposed structure, this can now be overcome. If the filtering, $\beta(z_0)B(z_1)$, is calculated in floating point arithmetic, reconstruction will not be affected by any operations within the filter block prior to the summation.

Three steps are required to produce a field limited filtered image. First, we filter along the rows and columns of the downsampled image with $\beta(z_0)$ and $B(z_1)$, respectively. The result will be limited to the range $[-1, 1]$. Second, we limit the field to $GF(2)$ by thresholding the filtered image using

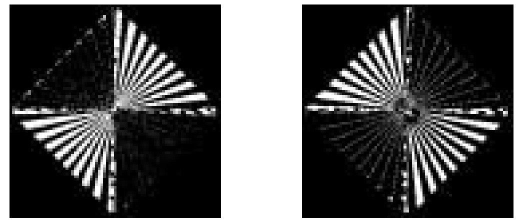
$$f(x) = \begin{cases} 1 & \text{if } x > 0, \\ 0 & \text{if } x \leq 0. \end{cases}$$

Finally, quantize the combination of this quantized image and the downsampled image with a new quantization function,

$$f(x) = \begin{cases} 1 & \text{if } x > 1, \\ 0 & \text{if } x \leq 1. \end{cases}$$

The transformation is now combined with the downsampled image in the upper branch using modulo-2 summation. The modulo-2 addition guarantees that the analysis band output remains $GF(2)$ or binary. This additional set of operations results in considerably less wrap-around distortion. As seen in Figure 4(a), the binary output is comparable to the grayscale output.

In fact, it even manifests greater visually suppression of directional information. We continue to the second stage to form the other direction. The next stage also filters the image with $\beta(z_0)B(z_1)$ and uses a similar thresholding function to quantize. Figure 4(b) shows that the other angle is



a b

Figure 4: Two-band binary decomposition shown in (a) and (b).

represented in the binary image and is similar to (in fact even better than) the grayscale output band.

As previously mentioned, reconstruction is performed by using a similar transformation and adding the inverse to the band output. To achieve perfect reconstruction requires a reversal of the filtering order. That is, we must reconstruct the second stage prior to the reconstruction of the first stage. All operations are performed modulo-2 resulting in an output image $\widehat{x}$ matching the input image x.

4. EXAMPLES AND APPLICATIONS

This directional filter bank can be extended to more bands than two and can provide a useful representation for analysis applications. Similar to a conventional rectangular decomposition, this can be achieved by using a tree structure. In this work, we employ a four band decomposition using a tree structure, like the one discussed in [6] for floating point systems.

There are several applications areas where directional filter banks (DFBs) are useful, such as computer vision, image analysis, and image enhancement. Image processing systems sometimes use directional filter banks as a basis for the orientation analysis stage. For example, image detection and feature enhancement of systems have typically contained a stage where the energy of different angular features is determined followed by an application dependent processing. In [14], the author applied DFB-based processing to detect linear features and enhance both fingerprint and cell images.

Linear feature detection in noisy images had previously been performed using a Radon transform [15]. Radon transforms, however, are not exactly invertible for discrete images. The lack of invertibility may lead to undesirable distortion during an analysis/synthesis enhancement process. Bamberger [14] applied DFBs successfully to linear features in fingerprints. However, this body of work was all done in the context of infinite precision arithmetic. The new binary DFB provides an alternate more efficient way of achieving similar results.

Indeed there are many ways in which a binary DFB tool could be employed for fingerprint enhancement. How one uses the binary DFB should be governed by the specific artifacts in the fingerprint one wishes to suppress or enhance. For example, smudges or ink blobs might be present in the original, arising from a non-ideal acquisition process. In such case, the location of the ink blob can be targeted and its presence removed using the DFB. Similarly, the DFB

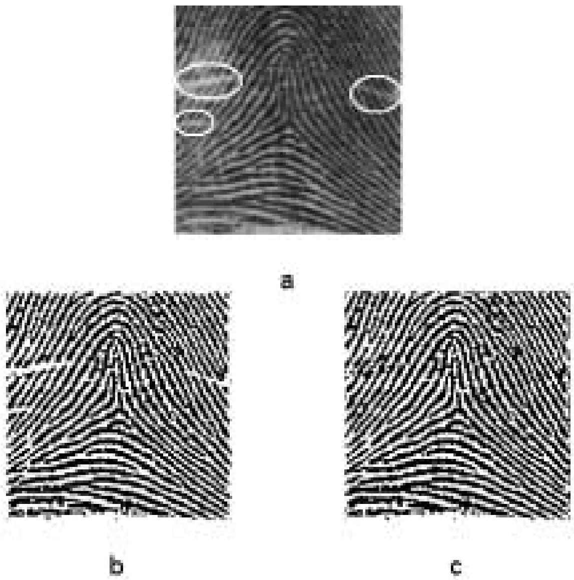


Figure 5: (a) Original fingerprint image. (b) Binarized image. (c) The enhance fingerprint image.

could be used to enhance the directionally dominant ridges, thereby reducing the effects of smudges. As an example of enhancement processing using the binary DFB, we consider here the problem of removing three scars in the fingerprint as shown explicitly in Figure 5(a). For the purposes of illustration, let's assume these markings occurred accidentally through a cut after the original recorded fingerprints were taken. Thus, we wish to remove these markings prior to matching. First, we split the input $x[\mathbf{n}]$ using a four band directional decomposition. We next segment the image into its dominant components and those comprising artifacts. For the purposes of this paper, we have performed this manually but techniques exist that automate the process [7].

The subbands are treated as a set, noting that one subband in the region of the scar is associated with ridges that we wish to preserve, while another subband (the horizontal component in this case) is associated with the scar. By weighting the horizontal subband coeffient with a gain of approximately zero in the region, and resynthesizing the binary image using the binary DFB bank, we can suppress the effects of the scar. This is shown in Figures 5(b) and (c), where 4(b) shows the binary original and 4(c) shows the output after enhancement, when one sees that the effects of the scar have been dramatically reduced.

5. CLOSING REMARKS

The binary DFB has the attractive property of allowing directional information to be displayed visually in the subbands. Moreover, its reconstruction process is well behaved and allows subband modifications to be made while enabling good quality reconstruction. Thus, the binary DFB can find application in fingerprint enhancement by providing the capability to perform region target suppression of artifacts and pattern feature enhancements.

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