Unless you try to do something beyond what you have already mastered, you will not grow!

-Ralph Waldo Emerson

5

Discrete Cosine Transform - A frequency domain based approach

5.1 Preamble

In the previous chapters, we have proposed several methods in spatial domain and analyzed their accuracy/ and suitability for off-line signature verification. They include the appearance based and grid based approaches. Our experimental studies revealed that the appearance based approaches exhibit better performance when compared to grid based approach. However, these approaches suffer from expensive computations and depends on the pixel density. Hence, in this chapter, we propose a transformation based approach. The principle advantage of transformation is the removal of redundancy between samples. This leads to uncorrelated transform coefficients, which can be encoded independently. The efficiency of a transformation scheme can be directly gauged by its ability to pack input data into as few coefficients as possible. This allows the quantizer to discard coefficients with relatively small amplitudes without introducing visual distortion in the reconstructed image.

Among the many transformation techniques, Discrete Cosine Transform (DCT) is found to be one of the best data capturing technique with very few low frequency
components. Hence in our work, we propose to employ DCT on the preprocessed signature to form the feature vector using the DCT coefficients. The advantage of using the DCT is the ability to compactly represent an off-line signature using a fixed number of coefficients, which leads to fast matching algorithms. More importantly, the fixed length is better suited, or even necessary, in certain applications related to information theory and biometric systems.

In this chapter, we investigate the possibility of compact representation of off-line signature samples and hence reducing computational complexities of signature verification. This is achieved by using low frequency DCT components of the signature images. The efficacy is reported through classification based on SVM and MLP classifiers.

The rest of the chapter is organized as follows. In section 5.2, a brief overview of existing frequency domain methods are presented. A review on DCT is presented in section 5.3. Section 5.4 presents the proposed approach based on DCT. Experimental results and analysis on standard datasets are reported in section 5.5. The overall conclusions of the chapter are drawn in section 5.6.

### 5.2 Background

A common objective in signature verification is to find a good way of representing the signature at the initial stage. A key step in developing a good representation is to expose the constraints and remove the redundancies contained in pixel images of signature images. Transformation to frequency domain through DCT and/or Wavelets are the two well-known and widely used techniques for this task in computer vision.

Dimensionality reduction is essential for extracting discriminative features and reducing computational complexity in classification stage. For this purpose, the statistical approaches such as PCA (chapter 2) and KDA (chapter 3) are also used as dimensionality reduction tools. They also solely rely on the pixel density and its distribution in the image. Therefore, it is highly desirable to choose an optimal
domain implementation, where it alleviates at least few of the aforementioned limits by retaining their original merits.

With this backdrop, to further enhance the classification performance of off-line signature verification, frequency domain analysis are being employed. Few works have been reported to extract the frequency domain features for static signature representation in the literature. To list a few, Fourier transform [21], [24] and [59], Hardamard transform [63], wavelet transform [59], [25] and [23], Random transform [20] and Fractal transform [36]. Still none of the works have reported using DCT co-efficients for off-line signature verification although it excels on on-line signature verification [58].

Motivated by the above factor, in this chapter, we have proposed an approach in frequency domain using the DCT coefficients. This method overcome the limitation (high learning time) of PCA and KLD but still retain the benefit of accurate classification with lesser computational complexity.

### 5.3 A review on Discrete Cosine Transform (DCT)

The DCT is a popular technique in image processing and video compression which transforms the input signal present in the spatial domain into a frequency domain. We proposed to use DCT-II in our work introduced by Wang [88]. The forward 2D-DCT of $M \times N$ block image $f$ is defined as

$$C(u, v) = \alpha(u)\alpha(v) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \times \cos \left( \frac{\pi(2x+1)u}{2M} \right) \cos \left( \frac{\pi(2y+1)v}{2N} \right)$$  \hspace{1cm} (5.1)

and the inverse transform is defined as

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \alpha(u)\alpha(v)C(u, v) \times \cos \left( \frac{\pi(2x+1)u}{2M} \right) \cos \left( \frac{\pi(2y+1)v}{2N} \right)$$  \hspace{1cm} (5.2)
where

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{M}}, & u = 0 \\ \frac{2}{M}, & u = 1, 2, \ldots, M - 1 \end{cases}$$

(5.3)

and, $x$ and $y$ are spatial coordinates in the image block, and $u$ and $v$ are coordinates in the transformed image. It is a well known fact that the discriminative features are available in the top-left portion of the image, say of size $M \times N$, i.e., the most energy being compacted to the low-frequency coefficients. The size of the subset is chosen such that it can sufficiently represent the input signature image and help in verification later. The size of the subset may be quite small compared to the whole vector with all the coefficients in it. It was observed that the DCT coefficients exhibit the expected behaviour in which a relative large amount of information about the original signature image is stored/represented in fairly small number of coefficients ([31] [46]). The DCT coefficients, which is located at the upper left corner, holds most of the image energy and have considered for further processing. For instance, the top $10 \times 10 = 100$ DCT coefficients are enough to represent the signature image and hence considered as a feature vector in our approach.

5.4 Proposed approach

The proposed DCT based approach for off-line signature verification involves three major phases: preprocessing, DCT based feature extraction and classification using SVM and MLP classifiers.

In the preprocessing stage, the signature images are binarized using Otsu’s method to remove the complex background which might have occurred due to scanning, ink distribution, and so on. The noise intruded due to binarization is eliminated using a simple morphological filter resulting in a clear noise free signature image. This preprocessed image is transformed to frequency domain using Discrete Cosine Transform (figure 5.1) to extract the coefficients as the represen-
tative features of the signature image. Thus, these extracted features act as the source for training the SVM and MLP classifiers. The details are presented in the following subsections.

Figure 5.1 (a) Initial image (b) Binarised and Noise removed (c) DCT transformed image (d) Marked top-left block of the image (Feature block) (e) DCT coefficients selection in Zig-zag pattern

5.4.1 DCT coefficients extraction and knowledge base construction

Let there be $N$ samples $A_k$ ($\forall k = 1, 2, \ldots, N$) in the dataset. Using these samples, extract the low frequency coefficients using 2D-DCT (as explained in section 5.3). Let the 2D-DCT representation of the sample $A_k$ be $x_k$ ($\forall k = 1, 2, \ldots, N$). The low frequency components of $x_k$s are concatenated into a 1D vector and accumulated in columns of matrix $X$ of size $d \times N$, where $d$ is the number of DCT coefficients used to represent the signature pattern. In our work, the $10 \times 10$, totalling to 100 frequency coefficients are extracted as the representative features of the signature sample.

The above said procedure is carried on all the samples of the dataset including genuine and skilled forgeries. The feature vectors accumulated from all the samples in the dataset forms the DCT knowledge base, a source for further
5.4.2 Classification based on DCT features

Two well known classifiers, SVM and MLP are used for classification. The classification based on SVM and MLP are respectively discussed in B 1 and B 2. The classifiers are initially trained with varying number of samples considering genuine signature features as positive samples (class 1) and forgeries as negative (class 0). An adaptive threshold is considered for classification in MLP as the class weight values varies from 0 to 1. As discussed in our earlier chapters, two well suited metrics, FAR and FRR are used to proclaim the efficacy of the proposed approach.

5.5 Experimental results and analysis

The efficiency of proposed approach is presented in this section through a detailed and thorough experimentations under various test conditions. To exhibit the performance of the proposed approach, experiments have been conducted on standard datasets considering SVM and MLP classifiers. The details regarding these databases and evaluation procedures are given in Appendix A.

An additional attempt is done in this chapter by considering random forgeries, which resulted with FAR as 0. The idea is to demonstrate that a large dissimilarity exists between genuine and random forgeries compared to skilled forgeries and also to prove practically, the skilled forgeries acts as major threat in signature verification.

Two modes of experimentation are carried out in three different set up with varying number of samples for training the classifier and testing against the trained network. In experiment-1, classifiers are trained with few genuine and few skilled forgeries and tested against the remaining genuine and random forgeries of the respective classes in the dataset. In experiment-2, few samples of skilled forgeries are considered for training along with genuine samples and tested against the re-
maining samples of the class. The detailed experimental set up along with the results are presented in the following sub-sections.

5.5.1 Experimentation-1

In experiment-1, we started training the classifiers with first 5 genuine and 5 skilled forge samples from each signer of the dataset. Later, we extended the system with first 10 genuine and first 10 skilled forge of each signer. In addition, the classifiers are trained with first 15 genuine and first 15 skilled forge samples. The testing is done against the trained network with remaining genuine samples of the class along with the same number of random forgeries from the respective datasets. (Random forgeries are the genuine samples of other signers in the dataset) Experimentation-1 was carried out considering SVM classifier as the means of classification.

Table 5.1 gives the best performances of the DCT based approach on all the datasets considered and SVM as a classifier. The table also reveals the best results of both experiment-1 and experiment-2. In the proposed approach, 0% of false acceptance is reported when tested with random forgery on CEDAR dataset. This was observed when we trained the system with 15 genuine and 15 skilled forgeries and tested with remaining 9 genuine and 15 random forgeries for each signer. In the similar experimental set up when tested with skilled forgeries the false acceptance rose to 6.44, summarizing the fact that the skilled forgeries are still a major threat to signature verification compared to random forgeries. These facts are considered in our future approaches by training the classifiers with random forgeries and testing against the skilled forge samples. The low FAR exhibits the good performance of the approach as it avoids the forge to be accepted as genuine.
Table 5.1 Best performance of the DCT-SVM technique

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Experimented with genuine and random forgery</th>
<th>Experimented with genuine skilled forgery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metric</td>
<td>Accuracy</td>
<td>FRR</td>
</tr>
<tr>
<td>CEDAR</td>
<td>95 76</td>
<td>4 24</td>
</tr>
<tr>
<td>GPDS-160</td>
<td>96 29</td>
<td>3 70</td>
</tr>
<tr>
<td>MUKOS</td>
<td>94 62</td>
<td>5 46</td>
</tr>
</tbody>
</table>

5.5.2 Experimentation-2

Similar to experiment-1, the SVM and MLP classifiers are trained with varying genuine and skilled forge samples. But, the testing is carried out with all the skilled forgeries along with the remaining genuine samples of the class in the respective dataset instead of random forgeries. The classification is conducted using both SVM and MLP classifiers.

Table 5.2 reveals the experimental results conducted on CEDAR, GPDS-160 and MUKOS dataset with varying number of training and testing samples. All the experiments have been carried out using both SVM and MLP classifiers.

5.6 Conclusion

In this chapter, we have proposed transformation based approach for off-line signature verification. The major contribution in this work is that the proposed method utilizes the benefits of DCT to ascertain that the verification accuracy of the proposed approach is better when compared to earlier approaches. The number of features used for classification is 100, which is very much less compared to other approaches in literature. Hence revealing the fact that the better accuracies can also be achieved with lesser number of features representing the sample. We have carried out extensive experiments under several real time test conditions. We have used forge samples of both random and skilled type for this purpose considering the standard signature datasets.
Table 5.2 Overall performance accuracy (FAR and FRR) of the proposed DCT technique

<table>
<thead>
<tr>
<th>Classifier Dataset</th>
<th>SVM</th>
<th>MLP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CEDAR</td>
<td>GPDS-160</td>
</tr>
<tr>
<td>No. of Training samples / Metrics</td>
<td>FAR</td>
<td>FRR</td>
</tr>
<tr>
<td>First 5 Genuine + 5 Skilled Forgery</td>
<td>8.32</td>
<td>10.64</td>
</tr>
<tr>
<td>First 15 Genuine + 15 Skilled Forgery</td>
<td>6.44</td>
<td>7.28</td>
</tr>
</tbody>
</table>

Note: Testing samples are the remaining genuine signatures along with all the skilled forge signature samples of the respective datasets.