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Dynamic Time Warping Algorithm for Texture Classification

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ABSTRACT

In this paper, a simple yet robust algorithm for texture identification using Dynamic Time Warping (DTW) is presented. The input image is partitioned into a smaller size with the size of 32x32 as a template. Significant information (features) from the template and the test data is transformed into a 1-Dimensional (1-D) series sequence using 1D Discrete Fourier Transform (1D DFT). The features from the test data will be compared with the template using DTW. For preliminary studies, 7 texture images are used as the template and 2 test images are used to evaluate the proposed methodology and both testing show a promising result.

1. Introduction

A human can easily perceive and adapt the variability of the texture to analyze the image. Texture refers to the properties that represent the surface [1]. Texture analysis requires good features to differentiate the textures for segmentation, classification, and recognition. Various feature extraction and classification have been developed recent years. Numerous applications adopt texture analysis such as in medical image and texture signature. There are many feature extraction approaches and classification for texture analysis. In feature extraction, the well- known approaches are gray level co-occurrence matrices (GLCM), local binary pattern, Gabor filters, wavelets and other transform methods, independent component analysis (ICA) and region covariance matrices. In this work, the texture features are obtained from 1-D Discrete Fourier Transform. Afterward, the features are given as the input to the Dynamic Time Warping for the identification process.

Dynamic Time Warping (DTW) was initially introduced to recognize spoken words [2]. Since then it has been used and proved useful in different applications such as handwriting recognition [3, 4], signature verification [5-8], fingers print verification [9], face recognition [10, 11] and control system [12] and so on. In this paper, DTW is adopted to identify different types of textures.

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2. Proposed Methodology

An image of a texture from a data set has been defined. For each data set, the feature is extracted and transformed into a 1-Dimensional (1-D) series sequence using 1D Discrete Fourier Transform (1D DFT) as a template. This template is used as a reference to identify the type of texture in the test images from the data set. The test image is then will go through partitioning process. This process produces virtual partitions of an input image. Each partition is equivalent to the template image in size. In this work, the size is set to 32x32. For each partitioned region, significant information is extracted and converted into a 1-D vector sequence to be aligned with the reference (template) sequence by DTW. The partition that produces the best matches with the reference sequence is selected as the corrected the texture image. Fig. 1 presents the functional flow of the image processing strategy. All the steps stated above are described in the following sections.

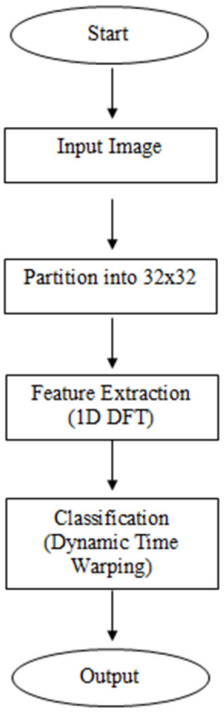


Fig. 1. Functional flow of texture identification process

2.1 Circular neighborhood 1-D Discrete Fourier Transform

The proposed method by [13] is adopted to extract the texture features. Assuming the center point S = s1, s2 is the center of a rectangular neighborhood Nr where Nr consists of 8 elements closest to S. If S is set to be at location (0,0), the coordinates of its neighborhood are {(-1,-1), (-1,0), (-1,1), (0,-1), (0,1), (1,-1), (1,0), (1,1)}. Based on Fig. 2, Nc represent the set of 8 circular locations which located 1 unit away from the center S. The element of Nc with the respect to the Cartesian rectangular coordinate are denoted by Nc = {(0, 1), (0, -1), (1, 0), (-1, 0), (,), (- ,-), (, -), (- ,). The intensities which do not fall on the rectangular grid are interpolated from the neighborhood

pixels using Euclidean distance or bilinear interpolation. Further reading for circular neighborhood 1-D Discrete Fourier Transform can be obtained in [13] in order to extract the features.

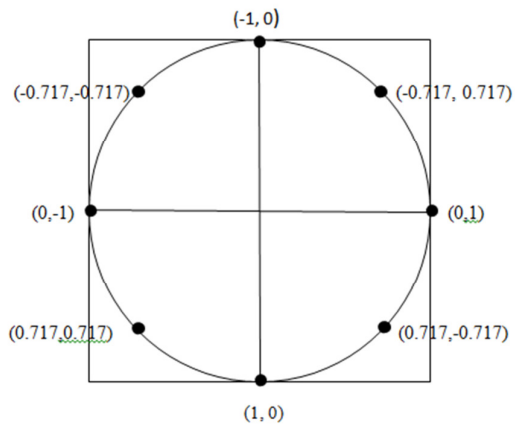


Fig. 2. Positions of the 8 elements of Nc

2.2 Dynamic Time Warping (DTW)

Dynamic Time Warping (DTW) is a fast and efficient algorithm for measuring the similarity between two sequences [14]. It is used to find the optimal alignment between two-time series, if one time series may be warped non-linearly along its time axis. The basic concept of DTW is to compute the minimum distance of two image templates by enumerating all possible accumulated distance until an optimal match is found [12]. Consider there are two sequences of feature vectors, template A and sample B with the length of n and m respectively.

$$A = [t_1, t_2, \dots, t_n]\,, B = [r_1, r_2, \dots, r_m] \tag{1}$$

The two sequences are then arranged in a matrix of size n×m with one on the top and the other on the left-hand side. To find the best match between these two sequences, an optimal warping path needs to be found which minimizes the total distance between them. An element in the matrix consists of the minimum distance of two points, ti and rj. The minimum distance of two points is expressed as:

$$D(i,j) = \min_k [D(i-1,k) + d(k,j)] \tag{2}$$

During calculation process of DTW the optimal warping path is still cannot be found yet, hence a traced back process proceeds when the end point is reached by getting the most minimum distance between two points.

3. Experimental Results

In this work, the four features (vectors) are obtained using 1-D Discrete Fourier Transform and is given as the input for the DTW to identify the texture. For each type of texture, a cropped input image and a template with the size of 32 by 32 are acquired. Then, based on the DFT, the

DTW will calculate the optimal path which has the least cost is associated with the correct type of texture. Figure 3 shows 7 texture images used in this paper.

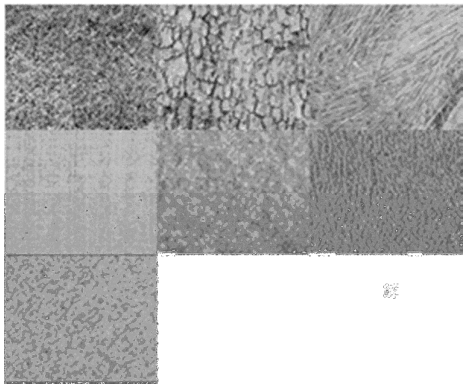
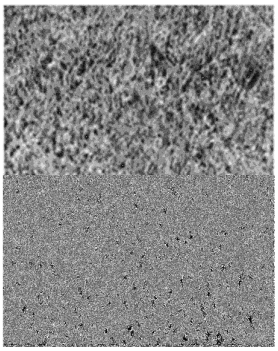
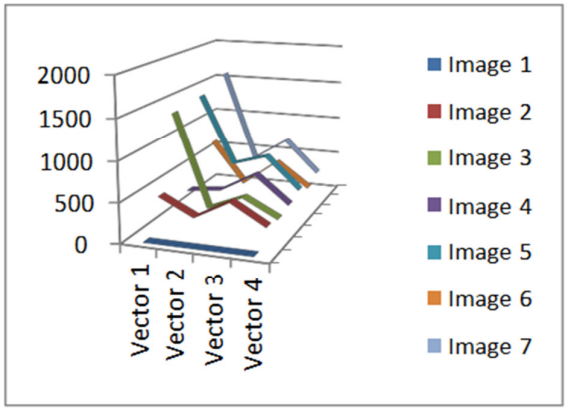


Fig. 3. Texture images

Figure 4 (a) shows the template image (reference image) and Fig. 4(b) shows the graph of the optimal path for all the features (vectors). In this experiment, 7 different images are used for testing. Fig. 4 (b) shows that the optimal paths for all the vectors are within image 1.



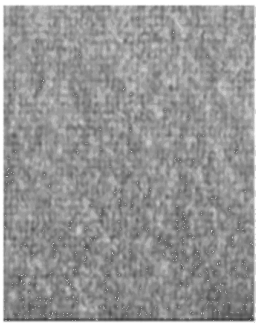
(a)



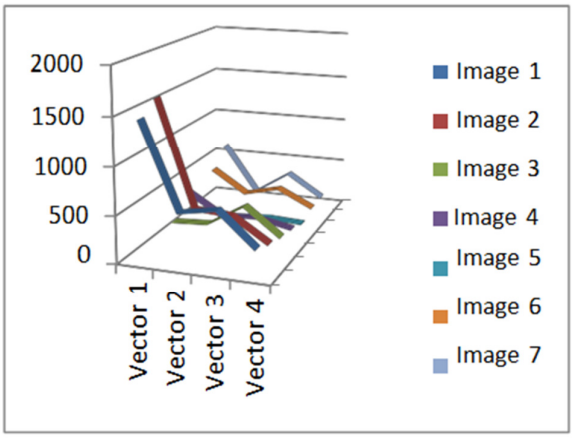
(b)

Fig. 4 (a) Template image and 4(b) The optimal path for four features for different images

Figure 5 (a) shows the template image (reference image) and Fig. 5 (b) shows the graph of the optimal path for all the features (vectors). Fig. 5 (b) shows that the optimal paths for all the vectors are within image 5.



(a)



(b)

Fig. 5 (a) Template image and 5 (b) The optimal path for four features for different images

4. Conclusion

In this paper, seven images are experimented and show promising results. Future work in progress is to improve the DTW method in order to implement a rotation invariant. Besides that, 1-D DFT is used to extract the features and DTW are adopted to identify the texture. Based on the result obtained, the DTW is simple yet can give promising outcomes to identify the texture.

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