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A New Approach for an Efficient DTW in Face Detection through Eyes Localization

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Introduction

Face detection in image is an important task for many applications. Some of the main applications are surveillance, eCommerce, face recognition, biometric and list goes on. However face detection is well known pattern recognition problem. Many methods and approaches have been proposed over the years but it is still a very challenging problem today [1]. It is a challenging task because of variability in scale, location, orientation, and pose. Facial expression, occlusion, and lighting conditions also change the overall appearance of faces [1–16].

Snake model has been proposed by Lam and Yan [2] for detecting face boundary. Wang et al [3] have employed genetic algorithm to detect human faces by calculating the projection of each face candidate onto the eigen faces space. Rowley et al [4] have improved a frontal face detection system based on neural network. Most of the mentioned face detection methods are feature based [4]. In such methods face is detected by detecting distinct face features and then measuring the geometric relations of human face. The drawback of such methods is the complexity and difficulty in translating human knowledge about the face to computer representation. Somya et al [7] introduced Correlation based face detection by using MACE filter . The design, analysis, and use of correlation pattern detection algorithms require background information, including linear systems theory, random variables and processes, matrix/vector methods, detection and estimation theory. Dervinis D. [5] introduced a hybrid method of geometry-based and image-based methods. This method extracts characteristic face points from 2D image and finds accurate coordinates. First they extracted the head contour from background and find the area with the eyes. Image-based methods finds accurate pupils centers with iris. They used Canny gradient method to get the lips and nose coordinates accurately. He extended his work in [6] to find the Head Orientation in image by using his technique introduced in [5] for extracting the characteristic face points from 2D image.. Different techniques and methods are being investigated to address this problem from different perspectives.

Dynamic Time Warping (DTW) is a fast and efficient technique for comparing and aligning two sequences of data points [10]. 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. This warping between the two time series can be used to determine the similarity. [10]. It is often used in speech recognition and has been quite efficient in other fields like data mining, environmental analysis, evolution of stock charts, robotics, gesture recognition, medicine, biometrics [8, 9]. Dynamic time warping algorithm is optimal similarity search method, but, it has been found that its limitations for accuracy are exposed when used in face features detection. Such limitations demand the need for supplementary methods to improve the detection rate of the algorithm.

In this paper, we present our technique of image processing and weighting strategies in applying DTW for face detection with different poses and variations. We elaborate through discussion and experiments' results that how our image processing strategy and weighting scheme applied to DTW algorithm effectively increase the performance and detection rate. In our technique, we use eyes localization for face detection that also helps in detecting faces with different poses and variations. Using such an approach does not require translation of human knowledge about the face to computer representation, training data set and training mechanisms or face geometry. This paper is organized as follows: we discuss the necessary steps for our image processing strategy and weighing scheme. Proceeding to next section, we present our approach of image partitioning, in next section we present dynamic time warping algorithm. Towards the end of this paper, results and discussion are put forward and conclusion is presented.

Image Processing Strategy to Dynamic Time Warping

The underlying premise of our approach is that the appropriate image processing operations and a weighting scheme is needed to maximize the performance of the DTW scheme for eye region detection.

Since eye region has the most edge information [11] in a facial image, it can be considered as a vital signature of a human face. Thus we choose an eye region cropped from a face image of a person as a template. Information is then extracted from this template and converted into a 1-D time series sequence to be stored as a reference. Given an input image of another person, probable eye regions are cropped from it. For each cropped region, information is extracted and converted into a 1-D vector sequence to be aligned with the reference sequence by DTW. The region that produces the sequence that best matches the reference sequence is selected as the eye region of the image. In the following sections, we describe all of the steps involved in the entire process of eye region detection (Fig. 1).

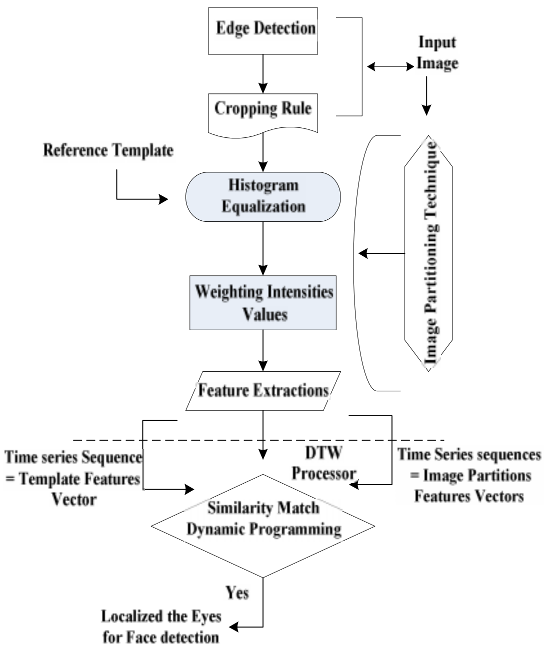

Fig. 1. Eye region detection process

Edge Detection

Given a head-shoulder gray scale image with plain background, the first task is to find the face where eye region is located. The first step is to perform edge detection. Standard sobel operators were used to find the boundary of the head presents in the image. Then cropping is done to remove other parts of the image including the background. Once the image is cropped, the next step is histogram equalization.

Histogram Equalization

Intensities in the images are highly sensitive to external factors such as, illuminations, pose, differences in skin colour, and etc. These external factors affect the distribution of intensities in the histogram of the images [12]. Histogram equalization can be applied to redistribute the intensities throughout the range. Fig. 2 and 3 show the histograms of an image before and after histogram equalization respectively.

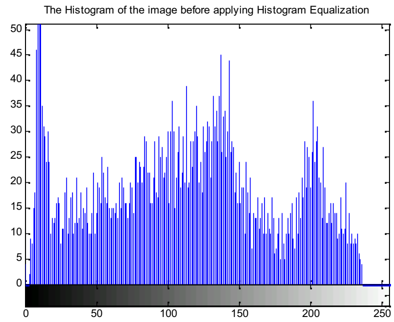

Fig. 2 Histogram of an image before equalization

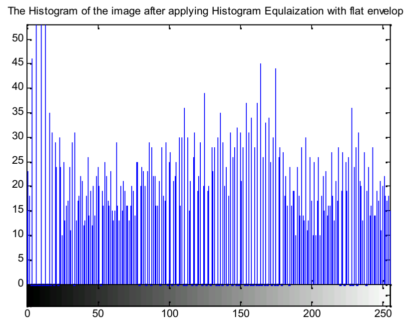

Fig. 3. Histogram distribution of an image after equalization

Weighting Scheme for Intensities Values

Projection technique is used in extracting features from image by transforming its matrix space into vector space. Horizontal and vertical projections are basically summing the pixels row by row and column by column. The sum of each row or column is assembled consecutively into a 1-D sequence. Normally, the 1-D sequences from horizontal or vertical projection are used directly as features [15, 16]. However, if the pattern shown by the pixel intensities in succession is important then summing them row/column-wise may suppress this vital information. We elaborate it with an example. Table 1 shows image intensity values of three columns and their respective sums.

Table 1 Example for image pixel intensities

Image Intensities values	171	181	200
	172	190	170
	188	200	190
	192	182	180
	202	172	185
Result of projection	925	925	925

Analyzing these intensity values shows that the first column exhibits an increasing trend while the second column shows a peak in the middle of the sequence. The third sequence shows no discernable pattern. However their projections (sums) are equal. To overcome this issue, we propose multiplying the rows and columns of the image intensities with a weighting function before summing them up. It is a function that produces an auxiliary image that will preserve some important sequential detail of pixel intensities of the original image. Additionally, the weighting function can be adjusted to accentuate certain features deemed vital in the image so that it will become more dominant during DTW similarity test. In fact, the columns and rows of the image can be multiplied with a few weighting functions of different characteristics if necessary.

It is observed that the middle region of the eye template is brighter than its right and left areas containing the two eyes and eyebrows. This high intensity area corresponds to the bridge of the nose. Therefore, we propose to multiply a simple saw tooth function with every row of the template to give emphasis on the middle columns where the nose bridge is present. Since the eyes are located in the middle rows of the template, we will multiply every single column of the eye template with a saw tooth function to give greater emphasis to the middle rows than the top and bottom rows. This weighting strategy imparts the most significance to the area of the nose bridge followed by the region containing the eyes. Fig. 4 shows a saw tooth function and an example of applying the saw tooth function to image template is shown in Fig. 5.

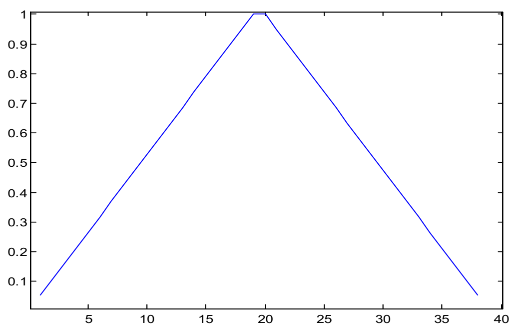

Fig. 4. Saw tooth function

The multiplication of each row and column with the saw tooth function can be done separately, row by row followed by column by column or otherwise. Then the projection is performed by summing up all the intensities that have been multiplied with weights (from the saw tooth function) in every column and row of the template. The sums are concatenated row-wise and column-wise to form two sequences. (1) and (2) are the projection in the horizontal (row-wise) and vertical (column-wise) direction

$$Proj_H(\boldsymbol{k}) = \sum_{i=1}^{N} C_{ik} * W_{ik}\,, \qquad (1)$$

where N is the total number of rows in the templae; C_{ik} is the intensity in column k; W_{ik} is 1 to 1 determinstic weighting function.

$$Proj_V(\boldsymbol{k}) = \sum_{j=1}^{M} C_{kj} * W_{kj}. \qquad (2)$$

For vertical projection (2), M is a number of columns, k is total number of rows. C_{kj} is the intensities in row k, W_{kj} is 1 to 1 deterministic weighting function. Fig. 6 and Fig. 7 show the results of row projections of image template T (used in our work) before and after applying our weighting scheme. The difference is quite obvious in both graphs. Fig. 8 and Fig. 9 show the results of column projection of image template T before and after applying the weighting scheme.

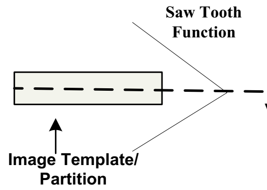

Fig. 5. Example of Saw Tooth Function being applied to image template/partition

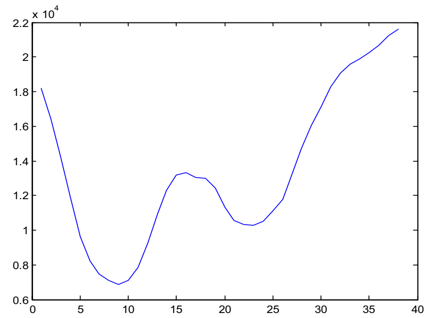

Fig. 6. Row projections for image template T before applying weighting

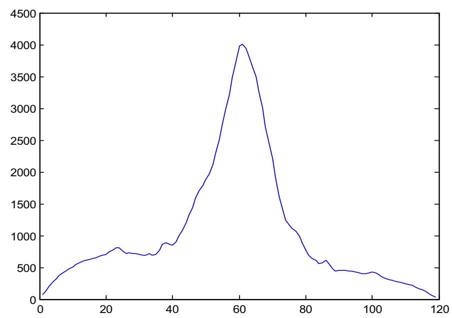

Fig. 7. Row projections for image template T after applying weighting

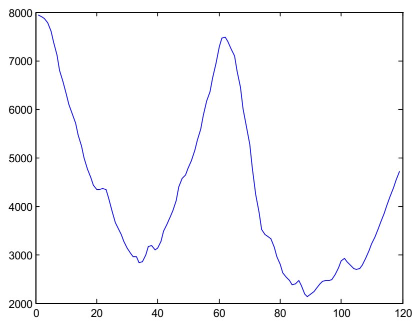

Fig. 8. Column projections for image template T before applying weighting

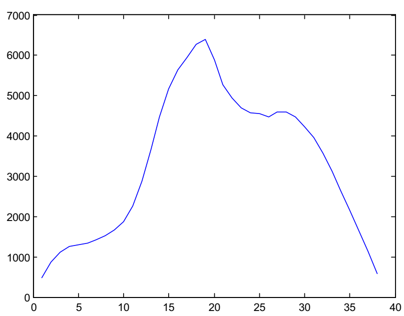

Fig. 9. Column projections for image template T after applying weighting

Features Vector Extraction

The row-wise and column-wise sequences obtained from the projections are joined together to form a single sequence where its length is M+N. In our experiment we have joined the last element of the row sequence to the first element of the column sequence

$$V = Proj_H \oplus Proj_V , \tag{3}$$

where $\oplus$ represents concatenation. Fig. 10 and Fig. 11 show the results of cocatnation without and with weighting scheme. It is obvious in Figurs 11 that our approach gives clear significance of peaks in feature vectors.

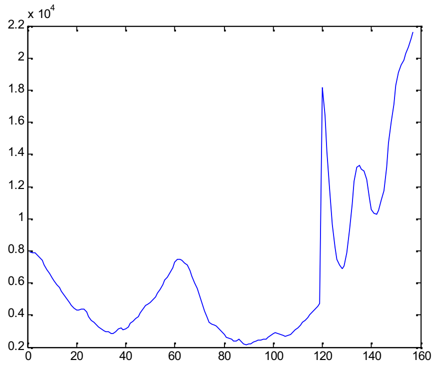

Fig. 10. Result of concatenation row and column projections for image template T before applying weighting

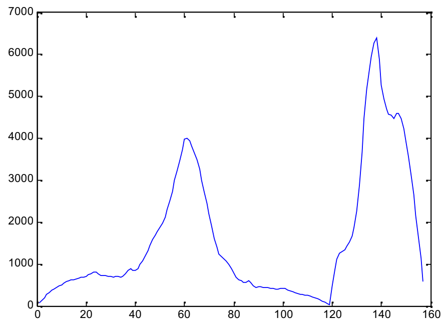

Fig. 11. Result of concatenation row and column for image template T after applying weighting

Dynamic Time Warping for Face Detection

Dynamic Time Warping (DTW) is an algorithm for measuring similarity between two sequences which may vary in time or speed. The DTW algorithm uses a dynamic programming technique to align time series with a given template so that a total distance measure is minimized [13]. The sequences for face detection using DTW are represented in vectors (a detailed description of DTW is beyond the scope of this paper, here we present the steps briefly).

Image partitioning is an important phase of our technique for face detection using DTW. It is applied only on test (input) image, which has been cropped through the steps of image processing strategy. An image partition is performed by our heuristic given in Fig. 12.

All partitions are equal in size of template image. Partitioning of an image is performed from the beginning of first row and column that continues till the last row and column. All image partitions as shown in Fig. 1 are further processed through the steps of our image processing strategy. These image partitions are transformed to feature vectors. At this point DTW algorithm is used to measure the similarity between the template features vector and partition features vectors.

```
//initialization
T= template image;
I= test image;
k=0;

[Trow,Tcol]=size(T);
[Irow,Icol]=size(I);

imax=Irow-Trow;
jmax=Icol-Tcol;

//iterations
  for every i from 1 to imax
   for every j from 1 to jmax
       increment k
       partition   I →Ipart=I(i:i+Trow,j:j+Tcol);


  repeat for i
  repeat for j
```

Fig. 12. Heuristic for image partitions

The first step of DTW for face detection is to compare each point in template feature sequence *(T)* with every point in the partitions' features sequences *(P)* on a m-by-n matrix where every element *(i,j)* of the matrix contains the distance *d(Ti,Pj)* between the points *Ti* and *Pj*. A warping path *W* (4) and (5) [13] defines the mapping between two sequences *T* and *P*. It is a contiguous set of matrix elements that minimizes the distance between the two sequences:

$$W = w_1, w_2, \ldots\ldots, w_k \quad max(m,n) * k * m + n, \tag{4}$$

$$W_k = [i_k, j_k], \tag{5}$$

where i_k and j_k denote the time index of trajectories *T* and *P*. The DTW warping path is constrained [14] in order to find the optimal shortest path. Some of the main constraints are: boundary constraint that limits the such that starting at $w_1 = [1,1]$ and finishes at w_k [m, n], continuity constraint that makes sure matching paths can not go backward in time, monotonicity constraint makes sure that points in the warping path are monotonically spaced in time. The path is determined by evaluating the cumulative distance *D (i,j)* (6) [13]. The *D(i,j)* is a sum of the local distance *d(Ti, Pj)* in the current cell and minimum of the cumulative distance in the previous cells

$$D(i,j) = d(T_i, P_j) + min[D(i-1, j-1), D(i - -1, j), D(i, j-1)]. \tag{6}$$

Once the eyes in an input image are detected after applying the processes defined above, it is inferred that the image is a face.

Experiment and Results

We conducted the experiments in different settings to evaluate the efficacy of our approach. Here, we present the results of applying DTW algorithm on our data set with and without using our weighting scheme and image processing strategy. The proposed algorithm is implemented in Matlab 7.4 running on a computer with 2.0GHz dual core OPTERON processor and 1.87GB RAM. The face image database was obtained from the University of Bern, Switzerland, which are of size 512×342. The database has 150 face images. In first setting, we applied the technique for face detection using DTW without our image processing strategy and weighting scheme, the detection rate was 69%. In second setting, we applied our image processing strategy with DTW algorithm on the same dataset, the detection rate improved to 86 %. In third setting, we applied image processing strategy and weighing scheme with DTW, the detection rate increased to 95 %.

Fig. 13 shows the face image, where the eyes have not been detected correctly. In this image intensity distribution was affected due to the light effect on left side.

Fig. 13. Before applying image processing strategy

With our experimental analysis and observation, histogram equalization reduced the effect of light on intensity distribution. The same image was detected correctly after applying our image processing strategy, Fig. 14 shows the result.

Fig. 14. After applying image processing strategy

Fig. 15. Before applying weighting scheme

Fig. 16. After applying weighting scheme

After applying our image processing startegy, detection rate was increased but there were some faces, which were not detcted due to the variations of poses. We applied our weighting scheme that provided eyes region more significant values and helped improving the detection rate. Fig. 15 shows the image faces whihc were not detected due to the variation of poses. Fig. 16 shows the same faces, which are correctly detected, after applying our weighting scheme.

Conclusions

1. An innovative approach of face detection method by supplementing dynamic time warping has been presented.
2. An image processing strategy has been discussed and shown that enhances the performance of DTW face detection method.
3. A weighting scheme to solve the problem of insignificant intensities of projection vectors has been presented that helps in getting high accuracy in matching process.
4. Results of using our image processing strategy and weighting scheme with DTW have been shown and discussed.
5. Future work involves the improvement of DTW algorithm and Dynamic Programming constraints to further increase the detection rate.

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This paper presents an innovative method of face detection by supplementing dynamic time warping algorithm with proposed image processing strategy and weighting scheme. Using our proposed approach overcomes some of the shortcomings in applying dynamic time warping for face detection, hence improving the performance and detection accuracy. The results presented and discussed in this paper show the efficacy of our approach in using DTW for face detection. Ill. 16, bibl. 16, tabl. 1 (in English; abstracts in English and Lithuanian).

S. Adwan, H. Arof. Dinaminio laiko iškraipymo algoritmo efektyvumo tyrimas veido detekcijai naudojant akių padėtį // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2011. – Nr. 2(108). – P. 103–108.

Pristatomas naujas veido detekcijos pagal akių padėtį metodas, paremtas dinaminiu laiko iškraipymo algoritmu. Taikant šį metodą galima išvengti kai kurių dinaminio laiko iškraipymo metodo trūkumų ir kartu padidinti detekcijos tikslumą ir sistemos našumą. Il. 16, bibl. 16, lent. 1 (anglų kalba; santraukos anglų ir lietuvių k.).