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MSNN based techniques for Face and Eye Recognition

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***Abstract*—** The accurate technique of face recognition effects the performance of a face detection system. An accurate eye localization system is required for better results. There are various techniques for Face and eye detection but MSNN technique is used for the experiment.

This technique consist of different stages: the first stage extracts features using morphological operations; the second stage performs classification of outputs from the last feature extraction layer.
For Eye detection we conducted another experiment by choosing different images .All the images are tested by sequential programme. Hit Miss Transform is used for grey scale images to extract the information from face. MSNN is well efficient from other techniques.

MSNN gives us a proper approach for images that are poor in visibility.
The combination of results gives us proper face and eye detection results.

Keywords—Neural Networks, MSNN, grey scale imaging, Face Recognition, Eye Recognition,

I. INTRODUCTION

Neural Network techniques have been used to identify people in one form or another over 100 years, as they relate to an individual's unique physical characteristics. They can never be forgotten, lost or copied, like a card or password and have been widely accepted as a fast, accurate and dependable way of, providing that it is moving into our everyday lives.

There are many areas in which face recognition can play a major role. Some are not necessarily high security applications, but face recognition can help to overcome a large number of unsolved identification problems, particularly in areas where instant face recognition is needed. Some examples are given in [5]:

- **Security systems at public places.**

Visitors have to be verified so that identities may not be swapped during visits.

- **Identification of licenses.**

Some drivers have fake licenses or they swap licenses among themselves to cross state borders.

- **Identification.**

Face recognition can be used to identify criminals or fugitives at the airport.

Face recognition has two main security applications: *verification* and *identification*.

Verification is simply a one-to-one match that may be performed quickly and generates a true or false result. The system compares the features of the given image with the contents of its database, resulting in a match or no match according to predefined parameters. Identification allows the user to submit a live sample and the system attempts to identify the person by using the image library within the participating databases. The result may be a set of possible matches, ranked with respect to closeness to the given query.

Here are the more common feature extraction and classification methods:

- Eigen faces
- Hidden Markov Model
- Principal Component Analysis
- Support Vector Machine

- Probabilistic Decision-based Neural Network
- Convolution Neural Network
- ARENA

The purpose of face recognition is to examine and extract information from a set of images and try to find the exact match of a given image. For such a system to recognize well, any extracted feature has to be accurate. Image processing is therefore used to eliminate unwanted information and extract useful features from an image. Machine vision systems make use of image processing techniques to carry out object identification and categorization. They can be classified according to their purposes [15]:

- Enhancement (to improve visibility)
- Segmentation (to separate regions)
- Classification (to classify segmented objects or features)

II. Morphological Operations

Morphological operations [19] are nonlinear mask operations that can detect shapes. The word *morphology* refers to *form* and *structure*, but in digital image processing, it refers to the shape of a region. Mathematical morphology is mainly based on set theory. It is about adding or removing pixels from a binary image according to certain rules depending on neighbourhood patterns. Dilation, erosion, closing, and opening are the more common morphological operations. As the names indicate, a dilation operation enlarges a region, while erosion makes it smaller.

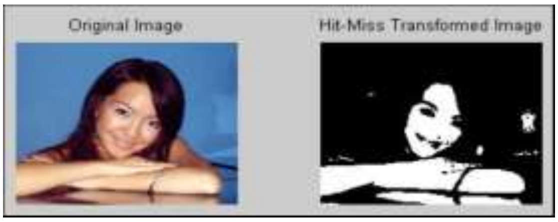
Morphological operations are part of image enhancement. Their application in MSNN is special because they are included in the learning algorithm of the back propagation network instead of occurring before it as a separate process. With such a network, Won [2] noted that sometimes image pre-processing is not necessary at all. Raw images can be fed directly as inputs.

III Hit-and-Miss Operation

The *hit-and-miss* operation [19] is another form of dilation-erosion-based convolution. It is a morphological shape detector that can be used to look for particular patterns of foreground and background pixels on an image. This logical process *and* an image to a structuring element. A hit-and-miss operation has the following equation [21]: $F\ K = (F\Theta K_1) \cap (F^c\Theta K_2)^c$,

$K_1 \cap K_2 = \quad , K_1 \quad K, K_2 \quad K$

Image *F* is first eroded with a structuring element *K1*. The image's complement is then eroded with a second structuring element K_2. This operation preserves pixels whose neighbourhood fits the shape of K_1 but doesn't fit the shape of K_2. K_1 and K_2 represent the shape of interest and the background respectively. They can be kernel sets generated from a larger kernel *K*. An example of a hit-and-miss output image is given below.



Selection of Face Database

During planning, we did some research on the Internet and found a few face datasets. Most were freely available and had a rich variety of pose types, but we have to keep to our objective. Our objective is to test MSNN on passport-sized images. They must be close-up shots, big enough, front view, and full-faced images. We finally decided on the face images kept by the Olivetti Research Laboratory [17]. The reason is that they are good in quality and not too small, which is suitable for us to perform eye detection.

We are clear that training and analyzing too many images is a waste of precious time, so we select 10 sets out of the available 40, each belonging to a different individual. In each of these sets, there are 10 face images. Each of them varies in orientation and expression, some with glasses, and some without glasses. We also came to know that these images were taken over a period of time. Although such differences are not very significant, we expect to see MSNN generalize implicit changes in a person.

IV Image Resizing and Pixel Arrangement

The original ORL images are 112 by 92 pixels in dimension, which means each has a total

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pixel size of 10304 if we place them in a single array row. This size is not efficient for normal training, especially when we have large training sets. To avoid increased computation and long training times, it is necessary to resize the face images.

Our images are therefore resized to 30×30 pixels immediately after they have passed through the *hit* and *miss* kernels - that is, before entering the classification stage. CB 4 is an example of the instruction loop that performs this action. The procedure reads in images from F1, resizes them, and organizes every image into rows. Since each subject has an equal number of 4 face images in the training set and the test set, their input dimension to the MSNN is the same: 4 rows×900 columns pixel units. Each subject is trained individually.

```
% read images rez=30;
……
for i = from:length
  temp = imread(['C:\images\f1\' num2str(i)
  '.tif']); temp = imresize(temp, [rez rez]);
  data1(i,:) = temp(:); end;
```

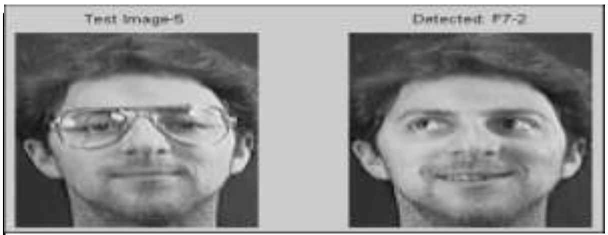
……*Code Block 4: Image resizing and organization for neural training [34].*

V Creation of Target Vectors

A target vector indirectly identifies a person. We use a four-value array format for our target outputs. Each target vector has a different combination of 0s and 1s. It is always important to choose target values that are within the range of the sigmoid activation function. If not, the algorithm would drive the free parameters to infinity and slow down the learning process. The subjects are identified by their folder names: F1 to F10.

F1: 0 1 1 0 F2: 1 1 0 0 F3: 1 1 1 0
F4: 0 1 1 1 F5: 1 0 0 0

F6: 0 0 0 1 F7: 1 0 1 0 F8: 0 1 0 1
F9: 1 0 0 1 F10: 0 0 1 1



A correct recognition by the MSNN.

VI Conclusion

In conclusion, we have shown that the morphological shared-weight neural work can approach the robustness needed for face recognition. Although it trained slower than the normal multilayer network, it exhibited better generalization than the back propagation network in terms of accommodating noise and gray-level shifts. Both performed equally well at detecting raw images, but the MSNN maintained stability and performance under greyscale variation.

We have also investigated the effects of training parameters on the MSNN. Experiments were carried out by altering the size and shape of the structuring element, the learning rate, the number of hidden neurons, and the types of sigmoid functions. The MSNN is not very responsive to structuring element size and shape; however, for training face images, the "disk" structuring element should be used, and its size should not be too large. The ideal size is 3×3 pixels for the standard ORL 112×92 image. The optimal value for our learning rate is 0.25, which produces the best performance in both face recognition and eye recognition. For the MSNN structure, the best number of hidden units is 10, while the best combination of sigmoid functions is the logistic function for both the hidden and output layers.

Our MSNN borrowed the same concept created by Won [1]. He used it for target detection, whereas we used it for face recognition. Our MSNN is also a cascaded network that consists of a feature extraction layer and a feed forward network. Raw face images are under sampled to minimize computation intensity and input into the feature extraction layer. Feature extraction is performed over the entire face image, where all the pixels are mapped to a feature map using greyscale hit-miss transform.

This feature map is a composite of eroded and dilated facial features. The hit weight is actually the structuring element for performing erosion; similarly, the miss weight is the structuring element for performing dilation. When the face image has passed through both these kernels separately, the eroded output and the dilated output are subtracted to obtain the difference matrix. This difference matrix forms the feature map.

Next, the feature map is fed into the back propagation network. The *net* sums entering the neurons are increased by adding a bias. They are then transformed into output by sigmoid. The output is subtracted by the target vector, and this error is used to calculate the correction term for the output layer. Since the network has one hidden layer, the output correction term is passed back to this hidden layer, which uses it to calculate its own correction term. Weights are then adjusted respectively at the output layer and the hidden layer. The final set of weights is then multiplied and sigmoid-transformed again with the original input to derive the final output for the entire training. This final output is later processed by another subprogram to compare against its prescribed threshold. If it falls within that range, the identification is confirmed.

Image similarity computed by existing mathematical metric is not always consistent with the human perception. For instance, Euclidean distance may not effectively preserve the perceptual similarity due to the subjectivity of perceived similarity with respect to the related task and database.

Therefore, designing effective feature extraction procedures is not an easy task. A good feature set makes the later part of the training and decision-making simpler and more accurate. The strength of the MSNN is in its translation-invariant extraction layer. It enables the network to learn complex patterns by extracting progressively more meaningful features from the input patterns of a face. The MSNN thus avoids being too restricted by mathematical metric in its classification process. This increases its ability to generalize.

References:

- Mohamed A. Khabou and Laura F. Solari, *University of Florida/University of West Florida*, A Morphological Neural Network-Based System for Face Detection and Recognition, Ieee trans. pp.296-301, 2006.
- Face Detection in Complex Background Based on Skin Colour Features and Improved Ada Boost Algorithms, Zhengming Li, Lijie Xue and Fei Tan, IEEE Trans. pp.723-729, 2010.
- Constantine Kouropoulos , Frontal Face Authentication Using Morphological Elastic Graph Matching, IEEE Trans. on

image processing , vol. 9, no. 4,pp. 555-560, April 2000.

- ohamed A. Khabou and Paul D. Gader, Automatic Target Detection Using Entropy Optimized Shared-Weight Neural Networks, IEEE Trans. on neural network, vol. 11, no. 1, pp. 187-193 January 2000.

- *G. Scott,' R.H. Luke 111, M. Skubic, and J.M. Keller*, "Face Recognition with Morphological Shared-Weight Neural Networks," Dept of Computer Engineering and Computer Science Technical Report, University of Missouri-Columbia, 2002

Scientific Papers / Seminar Publications

1. Y. Won et. al., **Morphological Shared-Weight Networks with Applications to Automatic Target Recognition**, Electronics and Telecommunications Research Institute, Daejon, South Korea, 1995. http://www.ieeexplore.ieee.org/
2. Y. Won and P. Gader, **Morphological Shared-Weight Neural Network for Pattern Classification and Automatic Target Detection**, University of Missouri-Columbia, 1995. http://www.ieeexplore.ieee.org/
3. D. Haun, K. Hummel, and M. Skubic, **Morphological Neural Network Vision Processing for Mobile Robots**, University of Missouri-Columbia, 1997. http://www.ieeexplore.ieee.org/
4. U. Uludag and A. Jain, **Biometrics**, International Conference on Pattern Recognition, Department of Computer Science and Engineering, Michigan State University, 1999. http://biometrics.cse.msu.edu/
5. V. Starovoitov, D. Samal, and D. Briliuk, **Three Approaches for Face Recognition**, The 6-th International Conference on Pattern Recognition and Image Analysis, Velikiy Novgorod, Russia, 2002. http://www.ieeexplore.ieee.org/
6. L. Aryananda, **Online and Unsupervised Face Recognition for Humanoid Robot: Toward Relationship with People**, A. I. Lab, MIT, 2001. http://www.ieeexplore.ieee.org/
7. K. Jung, **Face Recognition Using Kernel Principal Component Analysis**, Michigan State University, 2001. http://www.ieeexplore.ieee.org/
8. J. Huang, X. Shao, and H. Wechsler, **Face Pose Discrimination Using Support Vector Machines**, George Mason University and University of Minnesota, 1998. http://www.ieeexplore.ieee.org/

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