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Kernel Perceptron Face Recognition

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Abstract
This paper presents kernel perceptron algorithm as a new machine learning approach for single face recognition task resolution by using as input set one dimensional vector constituted by the color pixel information of a binary face image. Simulation results shows high accuracy and efficiency.

Keywords. Face Recognition, Kernel Perceptron.

INTRODUCTION

The field of pattern recognition is concerned with the automatic discovery of regularities in data through the use of computer algorithms and with the use of these regularities to take actions such as classifying the data into different categories [1]. In this sense, face recognition can be understood as a classification problem in which face patterns are use to distinguish one person from another and because of the numerous challegenes facing the system, many approaches have beeen developed to carry out this task [2], including: Eigenfaces [3], support vector machines [4], Fisher linear discriminant [5], randomized trees [6], among others.

In this paper kernel perceptron classification algorithm for face recognition is presented. First, image processing scheme is explained along with the input set representing face image features. Then, kernel perceptron classification algorithm is described. Finally, simulation results and conclusions are presented.

Face Image Processing

In this section image processing scheme for face detection and features extraction is described.

For face detection, Haar classifier proposed by Viola and Jones [7], [8] was used. For data normalization, each face image is resized to (30 × 30). Then, gray face image values (from 0 to 255) are converted to binary image values (-1 or 1). A graphical scheme of the image processing is shown below Figure 1.

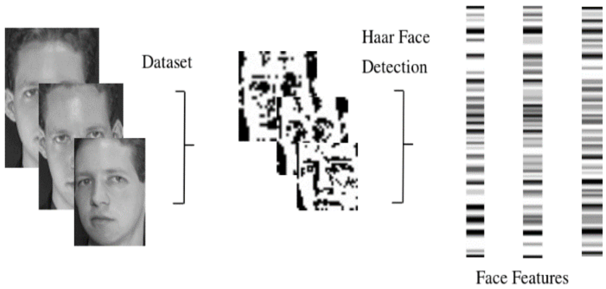

Figure 1. Image Face Features Extraction Graphical Gcheme.

Finally, feature vector is defined as the value average of each (5 × 5) set of neighborhood pixels values on the image. Feature vector extraction is shown in Figure 2.

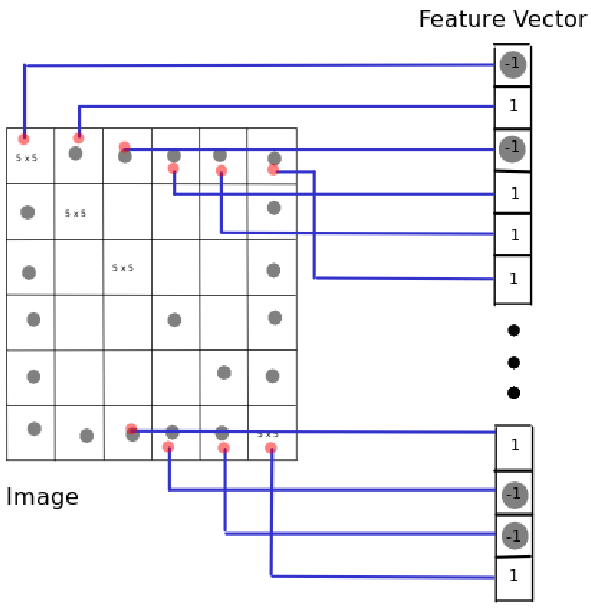

Figure 2. Feature Vector Definition

Kernel Perceptron

Kernel perceptron is a variant of the perceptron learning algorithm, introduced first in 1964 by Aizerman et al [9], that allows learning machines to classify non-linear separable data. Below, kernel perceptron used algorithm is described. Consider the simplest linear classification unit, the perceptron, described by its classification function given by:

$$f(x_i) = \phi(w \cdot x_i) \quad (1)$$

Where $x_i = (x_{i,1}, x_{i,2}, \dots, x_{i,n})$ is a feature vector that belongs to a sample set $X \subset \mathbb{R}^n$, $\phi : \mathbb{R}^m \to [-1, 1]$ is the activation function, where m is the output dimension and $w \in \mathbb{R}^n$ is the weights vector. A simple classification algorithm is described below in Table 1.

It can be seen that, for $w^0 = 0$:

$$w = \sum_{i=1}^{l} \alpha_i y_i \cdot x_i \quad (2)$$

Table 1. Perceptron Classification Algorithm

1	Let $X = \{x_1, x_2, \dots, x_1\}$, $Y = \{y_1, y_2, \dots, y_1\} \in [-1, 1]$ for l samples.
2	Iinitialize w^0
3	Take a tuple (x_i, y_i). If $f(x_i) \cdot y_i \leq 0$: $w^{k+1} = w^k + y_i x_i$
4	Update weights until $f(x_i) \cdot y_i > 0, \forall(x_i, y_i)$
	end

Where α_i is the number of errors committed for the i-th sample. Therefore:

$$f(x_j) = \phi\left(\sum_{i=1}^{l} \alpha_i y_i < x_i, x_j >\right) \quad (3)$$

where $< \cdot, \cdot >$ denotes de dot product over X. For the kernel perceptron algorithm, its necessary to introduce a kernel function $K: X \, x \, X \rightarrow \mathbb{R}$, such that:

$$K(x, x') = < \psi(x), \psi(x') > \quad (4)$$

Where ψ is mapping of X over a feature space **F** . This function allows to classify non-linear data by mapping features over high dimensional space where data is linearly separable. In this way, kernel perceptron algorithm stays as follows:

Table 2. Kernel Perceptron Classification Algorithm

1	Let $X = \{x_1, x_2, \dots, x_1\}$, $Y = \{y_1, y_2, \dots, y_1\} \in [-1, 1]$ for l samples.
2	Iinitialize α^0
3	Take a tuple (x_i, y_i). If $f(x_i) \cdot y_i \leq 0$: $\alpha^{k+1} = \alpha^k + 1$
4	Update α_i until $f(x_i) \cdot y_i > 0, \forall(x_i, y_i)$
	end

Simulation Results

Simulation results where made using the AT & T database [10]. Implemented Kernel perceptron uses radial basis function (RBF) kernel defined as:

$$K(x, x') = \exp(-\gamma \|x - x'\|) \quad (5)$$

With $\gamma = 1.1$. For training process two classes where defined for binary classification. First one containing the face images of a single person, and the other one containing face images of several different persons.

In Figure 3, is shown the minimun square error obtained on each iteration for a Training set and a Sample set.

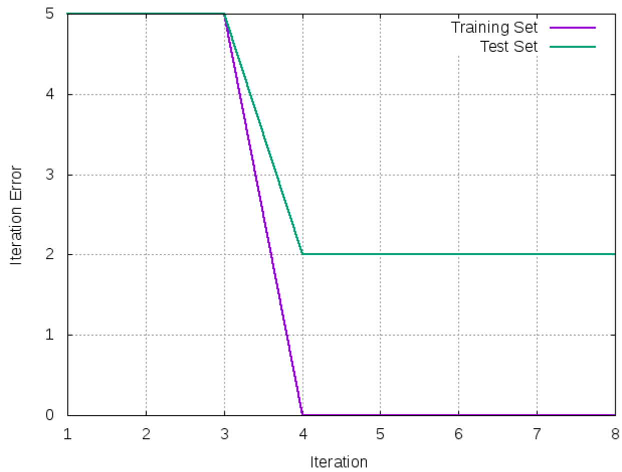

Figure 3. Kernel Perceptron learning: Minimun Square Error.

Below, in Table 3, obtained accuracies for the test set and the training set are shown.

Table 3. Kernel Perceptron Accuracy.

Set	Accuracy
Training set	100%
Test set	80%

CONCLUSSIONS

This paper presented a promising implementation of kernel perceptron algorithm for single face recognition. Results shows good accuracy for training and test sets, however it should be used to support individual recognition tasks where low computational cost is needed.

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