

Component Analysis in Artificial Vision

Oscar Déniz Suárez

University of Las Palmas de Gran Canaria, Spain

Gloria Bueno García

University of Castilla – La Mancha, Spain

INTRODUCTION

The typical recognition/**classification** framework in Artificial Vision uses a set of object features for discrimination. Features can be either numerical measures or nominal values. Once obtained, these feature values are used to classify the object. The output of the classification is a label for the object (Mitchell, 1997).

The classifier is usually built from a set of “**training**” samples. This is a set of examples that comprise feature values and their corresponding labels. Once trained, the classifier can produce labels for new samples that are not in the training set.

Obviously, the extracted features must be discriminative. Finding a good set of features, however, may not be an easy task. Consider for example, the face recognition problem: recognize a person using the image of his/her face. This is currently a hot topic of research within the Artificial Vision community, see the surveys (Chellappa et al, 1995), (Samal & Iyengar, 1992) and (Chellappa & Zhao, 2005). In this problem, the available features are all of the pixels in the image. However, only a number of these pixels are normally useful for discrimination. Some pixels are background, hair, shoulders, etc. Even inside the head zone of the image some pixels are less useful than others. The eye zone, for example, is known to be more informative than the forehead or cheeks (Wallraven et al, 2005). This means that some features (pixels) may actually increase recognition error, for they may confuse the classifier.

Apart from performance, from a computational cost point of view it is desirable to use a minimum number of features. If fed with a large number of features, the classifier will take too long to train or classify.

BACKGROUND

Feature Selection aims at identifying the most **informative features**. Once we have a measure of “*informativeness*” for each feature, a subset of them can be used for classifying. In this case, the features remain the same, only a selection is made. The topic of feature selection has been extensively studied within the Machine Learning community (Duda et al, 2000). Alternatively, in Feature Extraction a new set of features is created from the original set. In both cases the objective is both reducing the number of available features and using the most discriminative ones.

The following sections describe two techniques for Feature Extraction: Principal Component Analysis and Independent Component Analysis. Linear Discriminant Analysis (LDA) is a similar dimensionality reduction technique that will not be covered here for space reasons, we refer the reader to the classical text (Duda et al., 2000).

Figure 1.



As an example problem we will consider face recognition. The face recognition problem is particularly interesting here because of a number of reasons. First, it is a topic of increasingly active research in Artificial Vision, with potential applications in many domains. Second, it has images as input, see Figure 1 from the Yale Face Database (Belhumeur et al, 1997), which means that some kind of feature processing/selection must be done previous to classification.

PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA), see (Turk & Pentland, 1991), is an orthogonal linear transformation of the input feature space. PCA transforms the data to a new coordinate system in which the data variances in the new dimensions is maximized. Figure 2 shows a 2-class set of samples in a 2-feature space. These data have a certain **variance** along the horizontal and vertical axes. PCA maps the samples to a new orthogonal coordinate system, shown in bold, in which the sample variances are maximized. The new coordinate system is centered on the data mean.

The new set of features (note that the coordinate axes are features) is better from a discrimination point

of view, for samples of the two classes can be readily separated. Besides, the PCA transform provides an ordering of features, from the most discriminative (in terms of variance) to the least. This means that we can select and use only a subset of them. In the figure above, for example, the coordinate with the largest axis is the most discriminative.

When the input space is an image, as in face recognition, training images are stored in a matrix T . Each row of T contains a training image (the image rows are laid consecutively, forming a vector). Thus, each image pixel is considered a feature. Let there be n training images. PCA can then be done in the following steps:

1. Subtract the mean image vector m from T , where:

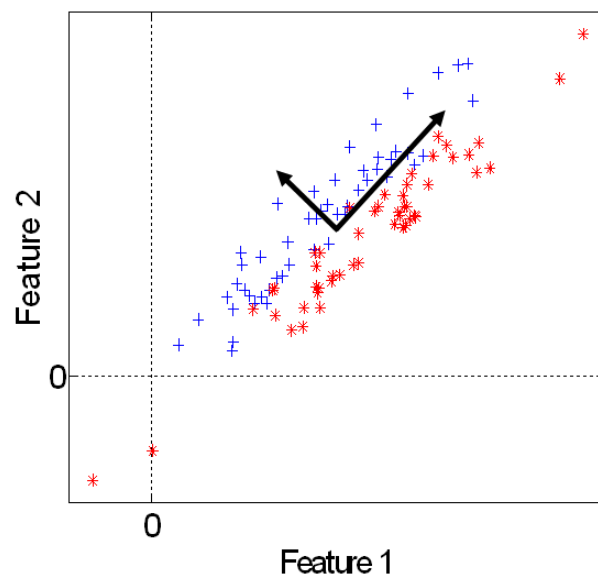
$$m = \frac{1}{n} \sum_i x_i$$

2. Calculate the covariance matrix C :

$$C = \frac{1}{n} \sum_i (x_i - m)(x_i - m)^T$$

3. Perform Singular Value Decomposition over C , which gives an orthogonal transform matrix W

Figure 2.



3 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-global.com/chapter/component-analysis-artificial-vision/10273

Related Content

Accounting for Individual and Situation Characteristics to Understand the User Behaviour when Interacting with Systems during Critical Situations

Yuska P. C. Aguiar, Maria de Fátima Q. Vieira, Edith Galyand Charles Santoni (2014). *International Journal of Ambient Computing and Intelligence* (pp. 29-55).

www.irma-international.org/article/accounting-for-individual-and-situation-characteristics-to-understand-the-user-behaviour-when-interacting-with-systems-during-critical-situations/147382

Practical Implication of Generative AI in the Science and Art Imaging Process: Generative AI Is for Poets

Jean Constant (2026). *Powering e-Collaboration Through AI, Machine Learning, and Internet of Things* (pp. 165-192).

www.irma-international.org/chapter/practical-implication-of-generative-ai-in-the-science-and-art-imaging-process/390203

Multi-Agent Systems Integration in Enterprise Environments Using Web Services

Eduardo H. Ramirez and Ramón F. Brena (2006). *International Journal of Intelligent Information Technologies* (pp. 72-88).

www.irma-international.org/article/multi-agent-systems-integration-enterprise/2406

Securely Communicating with an Optimal Cloud for Intelligently Enhancing a Cloud's Elasticity

S. Kirthica and Rajeswari Sridhar (2018). *International Journal of Intelligent Information Technologies* (pp. 43-58).

www.irma-international.org/article/securely-communicating-with-an-optimal-cloud-for-intelligently-enhancing-a-clouds-elasticity/205669

Building Intelligent Multimodal Assistants Based on Logic Programming in the Meme Media Architecture

Kimihito Ito (2007). *Intelligent Assistant Systems: Concepts, Techniques and Technologies* (pp. 145-168).

www.irma-international.org/chapter/building-intelligent-multimodal-assistants-based/24176