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RESEARCH ARTICLE

AN EXPLORATION ON PRINCIPAL COMPONENT COMPRESSION SYSTEM FOR PASSENGER FIGURE IMAGES

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ABSTRACT

In light of the remarkable advancements in communication information technology and multimedia internet technology, there arises an increasingly demanding need for the proficient handling of image data pertaining to passenger luggage. This encompasses the critical aspects of image transmission, storage, and compression. The contemporary landscape of passenger figure images presents a formidable data magnitude, which poses considerable trials upon the constraints of limited bandwidth. Consequently, the implementation of digital image compression strives to capture the overarching characteristics of the images utilizing a diminished bit count, while concurrently minimizing the potential degradation during the subsequent image restoration process. The present study incorporates principal component analysis (PCA) in the context of the security inspection industry, specifically focusing on passenger figure images. The application of PCA is integrated within the research framework of image compression and reconstruction systems. In this regard, MATLAB software is utilized to simulate the experiments, followed by an in-depth analysis of the obtained results. The findings demonstrate that by ensuring a cumulative contribution rate of more than 85% from a select few principal components following variable dimension reduction, it is feasible to achieve clear and distortion-free passenger figure images.

KEYWORDS

Digital image; principal component analysis; figure image; compression system

1. INTRODUCTION

Digital image compression and reconstruction techniques have found widespread applications in various domains, such as industry, agriculture, healthcare, aerospace, and defense (Ruan, 2011; Yang, 2016; Xie, 2014). In the industrial sector, it is primarily used for non-destructive testing of products and components on production lines. In agriculture, it aids in disaster detection and land planning through satellite imagery. In healthcare, it facilitates cell classification, processing and analysis of medical microscopy images, and X-ray radiography. In the civil aviation industry, image compression plays a crucial role in handling a large volume of useful passenger figure images obtained from centralized screening stations for further intelligent analysis and identification.

The technique of compressing and reconstructing figure images has its roots in the digitalization theory of television signals proposed in the mid-20th century (Zhou, 2010; Wu, 2008; Liu et al., 2001). Over the course of more than 60 years, image compression and reconstruction techniques have been continuously improved and developed. In the late 1980s, significant advancements were made in image compression and reconstruction due to the emergence of various compression theories such as wavelet transform, Huffman coding, and artificial neural network theory. In recent years, with the rapid development of the civil aviation industry, there has been a noticeable increase in the number of passengers, which poses significant challenges in terms of storage, transmission, and centralized display of passenger figure images in smart security screening channels. Therefore, this study focuses on the research and analysis of a compression system for passenger figure images using principal component analysis.

2. FUNDAMENTAL PRINCIPLES OF PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a powerful and effective method of data analysis. Mathematically, it is a multivariate statistical technique that utilizes dimensionality reduction to transform multiple scalar indicators into a smaller set of uncorrelated principal components. These principal components capture the majority of the original information and can generally be expressed as linear combinations of the original variables (David, 2003).

The fundamental principle of PCA for dimensionality reduction is as follows: Let's consider a dataset with n samples, each containing p variables, and construct an $n \times p$ data matrix, denoted as $\boldsymbol{X}$, as shown in Equation (1).

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix} \quad (1)$$

As the number of variable (p) increases, analyzing problems in a p-dimensional space becomes increasingly complex. Therefore, it becomes crucial to apply dimensionality reduction techniques to high-dimensional matrices. In other words, the goal is to obtain a few meaningful composite indicators that can replace the original multitude of variable indicators while ensuring the obtained indicators reflect the information conveyed by the original variables to the maximum extent and remain uncorrelated with each other.

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Definition: The original variable indicators are denoted as x_1, x_2, ..., x_p, and the new variable indicators generated through dimensionality reduction are denoted as z_1, z_2, ..., z_m $(m \le p)$. These new variables are obtained by linear combinations of the original variables, as shown in Equations (2)-(3).

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_2 + \cdots + l_{1p}x_p \\ z_2 = l_{21}x_1 + l_{22}x_2 + \cdots + l_{2p}x_p \\ \quad \cdots\cdots \\ z_m = l_{m1}x_1 + l_{m2}x_2 + \cdots + l_{mp}x_p \end{cases} \quad (2)$$

$$l_{i1}^2 + \cdots\cdots + l_{ip}^2 = 1 \quad (3)$$

To determine the coefficients $\boldsymbol{l_{ij}}$, the following principles are applied:

(1) The variables z_i and z_j ($i \neq j$; i, j = 1, 2, ..., m) are mutually unrelated.

(2) By performing linear combinations of x_1, x_2, ..., x_p and selecting the combination that yields the maximum variance as z_1, further linear combinations of x_1, x_2, ..., x_p that are uncorrelated with z_1 are explored, and the combination with the maximum variance is denoted as z_2. This process continues, with zm being the combination that maximizes the variance among all the linear combinations of x_1, x_2, ..., x_p while remaining uncorrelated with z_1, z_2, ..., z_{m-1}. Consequently, the obtained new variable indicators z_1, z_2, ..., z_m are referred to as the first, second, ..., mth principal components of the original variable indicators x_1, x_2, ..., x_p.

Based on the aforementioned analysis, the essence of the PCA algorithm lies in determining the loadings $\boldsymbol{l_{ij}}$ of the original variables x_j (j = 1, 2, ..., p) on the principal components z_i (i = 1, 2, ..., m). Next, we will mathematically prove that they correspond to the m largest eigenvalues of the correlation matrix.

Let $\mathbf{X} = [X_1,\ X_2, \cdots, X_p]^T$ be a p-dimensional random vector, with mean $\mu = E(\mathbf{X})$ and covariance matrix $\sum = D(X)$. The p eigenvalues of $\sum$, denoted as $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_p$, correspond to the eigenvectors $t_1,\ t_2, \cdots, t_p$, respectively, as shown in Equation (4).

$$\sum \mathbf{t}_i = \lambda_i \mathbf{t}_i, \quad \mathbf{t}_i^T\mathbf{t}_i = 1, \quad \mathbf{t}_i^T\mathbf{t}_j = 0 \quad (i \neq j; \quad i,\ j = 1,\ 2, \cdots, \quad p) \quad (4)$$

Now, the following linear transformation is considered, as shown in Equation (5):

$$\begin{matrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{matrix} = \begin{matrix} L_{11} & \cdots & L_{1p} \\ \vdots & \ddots & \vdots \\ L_{n1} & \cdots & L_{np} \end{matrix} \begin{matrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{matrix} = \begin{matrix} \mathrm{L}_1^{\mathrm{T}} \\ \mathrm{L}_2^{\mathrm{T}} \\ \vdots \\ \mathrm{L}_n^{\mathrm{T}} \end{matrix} \mathrm{X} \qquad (n \leqslant p)$$

(5)

If we want to represent $\mathbf{X} = [X_1,\ X_2, \cdots,\ X_p]^T$ based on the principal components of $\mathbf{Y} = [Y_1,\ Y_2, \cdots,\ Y_p]^T$, we aim to maximize the variance $D(Y_i) = \mathbf{L}_i^T \sum \mathbf{L}_i$ of Y_i while minimizing its correlation. Furthermore, to capture as much original information as possible, the vectors Y_i and Y_j cannot contain redundant information, meaning the covariance should be $cov(Y_i,\ Y_j) = \mathbf{L}_i^T \sum \mathbf{L}_j = 0$. It can be mathematically proven that when $\mathbf{L}_i = \mathbf{t}_i$, the variance of $D(Y_i)$ is maximized, and its maximum value is λ_i. Additionally, Y_i and Y_j satisfy the orthogonal condition.

In practical applications, the overall covariance matrix of variable $\mathbf{X}$ is typically unknown and can only be estimated based on the available samples. Let $\mathbf{X}_1,\ \mathbf{X}_2, \cdots,\ \mathbf{X}_n$ represent a set of samples extracted from the population of $\mathbf{X}$. In this scenario, $\mathbf{X}_i = [X_{i1},\ X_{i2}, \cdots, X_{ip}]^T$, and the sample observation matrix can be denoted as follows Equation (6):

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_1^T \\ \mathbf{X}_2^T \\ \vdots \\ \mathbf{X}_n^T \end{bmatrix} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1p} \\ X_{21} & X_{22} & \cdots & X_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ X_{31} & X_{32} & \cdots & X_{3p} \end{bmatrix} \quad (6)$$

Each row in the matrix $\mathbf{X}$ corresponds to a sample, while each column represents a variable. Therefore, the sample covariance matrix $\mathbf{S}$ and the correlation coefficient matrix $\mathbf{R}$ can be defined as follows Equation (7):

$$\mathbf{S} = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{X}_i - \bar{\mathbf{X}})(\mathbf{X}_i - \bar{\mathbf{X}})^T = (S_{ij})$$

$$\mathbf{R} = (R_{ij}) \qquad R_{ij} = \frac{S_{ij}}{\sqrt{S_{ii}S_{jj}}} \quad (7)$$

Assuming the j-th principal component score of sample $\mathbf{X}_i$as $SCORE(i,\ j) = \mathbf{X}_i^T\mathbf{t}_j$, it can be represented in matrix form as follows Equation (8):

$$SCORE = \begin{bmatrix} \boldsymbol{X}_1^{\mathrm{T}} \\ \boldsymbol{X}_2^{\mathrm{T}} \\ \vdots \\ \boldsymbol{X}_n^{\mathrm{T}} \end{bmatrix} [\boldsymbol{t}_1, \boldsymbol{t}_2, \cdots, \boldsymbol{t}_p] = \boldsymbol{XT} \quad (8)$$

Taking the inverse of the above expression allows for the reconstruction of the original samples from the score matrix, as shown in Equation (9):

$$\mathbf{X} = \mathbf{SCORE} \bullet \mathbf{T}^{-1} = \mathbf{SCORE} \bullet \mathbf{T}^T \quad (9)$$

In the general case, PCA selects the first m principal components to approximate the original samples. To restore the original samples, it is sufficient to preserve the coefficient matrix $\boldsymbol{T}$ and the score matrix $\boldsymbol{SCORE}$. Let's consider an original sample size of $n \times p$. During data compression, by retaining only the first m principal components, the data volume decreases from np to $pm + nm$. Therefore, the data compression ratio can be calculated as $np/(pm + nm)$. A higher compression ratio indicates a more pronounced compression effect, but it also entails a higher loss of information. To assess the contribution of each principal component to the original variables, the concept of contribution rate is introduced. The contribution rate is obtained by performing eigenvalue decomposition on the data matrix, arranging the eigenvalues in descending order, and selecting the top N eigenvalues. We aim for the sum of these top eigenvalues, denoted as S_n, to account for 85% to 95% (an empirical range) of the total eigenvalue sum, denoted as S. As a result, N represents the number of principal components, while the contribution rate is defined as S_n/S (Liu, 2007; Qin and Zheng, 2011).

3. Implementation Process of Compression System

(1) The compression system based on PCA involves concatenation operations (Zhang and Liu, 2010; Zheng, and Miao, 2010; Wu, and Bi, 2007; Shang et al., 2002). In the experiment, a folder containing images of passenger figures was loaded as the target for compression. The compression and decompression processes were performed to evaluate the compression effect from both macroscopic and microscopic perspectives. By extracting principal components, calculating the score matrix, and analyzing the contribution rate, the compression performance was assessed. The following MATLAB code snippet demonstrates the implementation of principal component compression using the "pcasample" function. It takes as input the image matrix, configures the principal components, and specifies the block size for partitioning. The output includes the reconstructed 2D image matrix, compression ratio, and contribution rate.

(2) Conversion between images and samples: In general, digital images are treated as two-dimensional arrays. To transform an image array into a sample matrix, the image needs to be divided into sub-blocks. Each sub-block is then flattened into a one-dimensional vector, and all the sub-blocks are combined into a single sample matrix. Suppose the size of the image array $\boldsymbol{K}$ is 256×576, and the sub-block size is 16×8. Then, $\boldsymbol{K}$ can be divided into $(256/16) \times (576/8) = 1152$ sub-blocks. Each sample contains 16×8 elements. These samples are stretched into row vectors, and finally, the 1152 samples are assembled into a sample matrix of size 1152×128, denoted as $\boldsymbol{X}$.

4. Analysis of Experimental Results

Following the compression system process in the MATLAB simulation tool, an 24×24 image size was chosen to align with the original image dimensions. After conducting PCA, MATLAB programming was employed to observe the influence of various numbers of principal components (1, 6, 11 and 16) on the image compression effect. The specific results for the compression effects under different principal component parameters are presented in the following Fig. 1.

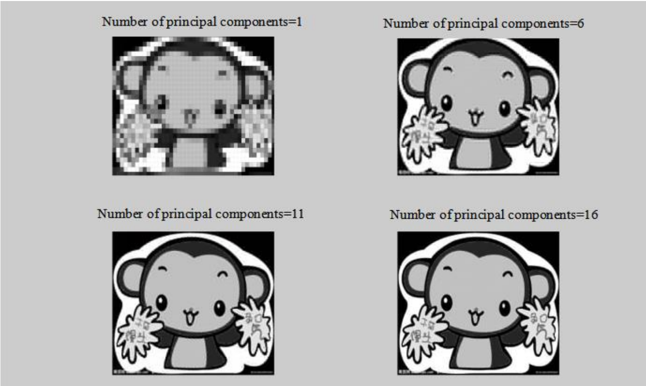

Figure 1: Image compression effects under different numbers of principal components

Through the analysis of Fig. 1, it can be observed that as the number of principal components increases, the image becomes progressively clearer. The aforementioned figure depicts an increase in the number of principal components, starting from a sub-block size of 24×24. Moreover, different numbers of principal components correspond to varying compression ratios. From the four images presented, it can be seen that when the compression ratio is less than 60, the image loss is not significant, and the distortion is imperceptible to the naked eye. The image compression effects of the passenger figure under different numbers of principal components are illustrated in Fig. 2.

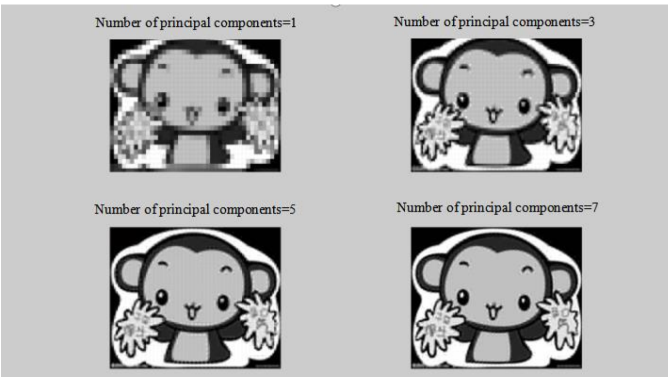

Figure 2: Image compression effects under different numbers of principal components

Through rigorous analysis of Fig. 2, it is apparent that when the number of principal components is reduced to 3 with a corresponding compression ratio of 132.7331, the image exhibits noticeable block artifacts while still preserving essential contour information. These experimental findings suggest that an increased number of principal components leads to a degradation in compression performance; however, it also results in a diminished loss of image information. Consequently, the selection of an appropriate number of principal components should be guided by practical considerations, aiming to achieve an optimal compression outcome.

Comparative evaluation of Figs. 1 and 2 reveals that when the increment of principal components is moderate, the image fails to attain the desired level of clarity. Significantly, Fig. 1 underscores the notable advantages of employing principal component analysis, exhibiting a higher compression ratio that correlates with more conspicuous compression effects and a commendable signal-to-noise ratio. Importantly, it is essential to emphasize that the application of principal components extends beyond singular sample variables. When applied to image data, it involves segmenting the image into coherent sub-blocks, treating them as interrelated samples, thereby acknowledging the iterative nature of their inherent components.

5. Conclusions

In the study of principal component analysis applied to compressing images of passenger figures, when the variables exhibit low inter-correlation, the dimensionality reduction effect of the principal components may not be significant. It is also possible that these variables possess nonlinear relationships. In practical applications, it is crucial to ensure that the cumulative contribution rate of the selected principal components, serving as the basis for variable reduction, reaches 85% or higher in order to obtain clear representations of the figures, facilitating the implementation of intelligent applications.

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