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PRESENTATION AND COMPARISON METHODS FOR SEMANTICALLY DIFFERENT IMAGES

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This paper discusses the methods of presentation and comparison for semantically unrelated images with assessment of their similarity in original feature space, and in Space of Canonical Variables (SCV). Comparison in original feature space is based on color histograms, phase correlation and structural similarity index. The projection of the source images in SCV is implemented using two-dimensional canonical correlation analysis algorithm presented in this paper, and the measure of their similarity in SCV is based on the phase correlation.

Introduction

In recent decades, biometric technologies of human recognition and analysis rapidly develop [1]. Very complex problems are solved by means of biometric technologies, for example, problem human-computer interaction or problem of brain-computer interface. These tasks include observation of a person from different, seemingly unrelated, angles, and use of information from these observations for the interpretation or understanding of other observations. That is why recently interests of specialists in computer science and pattern recognition were devoted to mathematical methods allowing to transform two unrelated sets of data from the original feature space into a new common features subspace in which the original data sets are highly correlated. These methods are based on projections Partial Least Squares (PLS) and Canonical Correlation Analysis (CCA). CCA method was presented by Hotteling in the 1930s and initially described relationship between two one-dimensional data sets [2] with forecast of its application to multidimensional data. Two problems were found when using CCA for processing of digital images. The first problem is related to multi-dimensionality of initial data - images as 2D objects, with the third dimension determining brightness and the fourth dimension defining color components. The second is related to the problem of Small Sample Size, when dimension of the original feature space significantly exceeds the number of images in the original sample [3].

2D CCA/2D KLT algorithms

Suppose that we are given two sets of input data consisting of K images of size $M\times N$ each:

$$X = [X^{(1)} X^{(2)} \dots X^{(K)}],\ Y = [Y^{(1)} Y^{(2)} \dots Y^{(K)}] \quad (1)$$

where $X^{(k)}, Y^{(k)}$ – pairs of images, wherein $MN \gg K$. We define the average images in each set of raw data:

$$\overline{X} = \frac{1}{K}\sum_{k=1}^{K} X^{(k)},\ \overline{Y} = \frac{1}{K}\sum_{k=1}^{K} Y^{(k)},\ k=1, 2, \dots, K.$$

If we assume that $\overline{X}^{(k)} = (X^{(k)} - \overline{X})$ and $\overline{Y}^{(k)} = (Y^{(k)} - \overline{Y})$, then instead of (1) we obtain:

$$\begin{aligned} \widetilde{X} &= [\overline{X}^{(1)} \overline{X}^{(2)} \dots \overline{X}^{(K)}] \\ \widetilde{Y} &= [\overline{Y}^{(1)} \overline{Y}^{(2)} \dots \overline{Y}^{(K)}] \end{aligned} . \quad (2)$$

Then we calculate eight covariance matrices $C_{xx}, C_{xy}, C_{yy}, C_{yx}$ for rows (r) and columns (c) of source images respectively [4].

To further implement CCA we calculate four total scattering matrices:

$$\begin{aligned} S^{(total\,1,r)} &= [C_{xx}^{(r)}]^{-1} C_{xy}^{(r)} [C_{yy}^{(r)}]^{-1} C_{yx}^{(r)}; \\ S^{(total\,2,r)} &= [C_{yy}^{(r)}]^{-1} C_{yx}^{(r)} [C_{xx}^{(r)}]^{-1} C_{xy}^{(r)}. \end{aligned} \quad (3a)$$

$$\begin{aligned} S^{(total\,1,c)} &= [C_{xx}^{(c)}]^{-1} C_{xy}^{(c)} [C_{yy}^{(c)}]^{-1} C_{yx}^{(c)}; \\ S^{(total\,2,c)} &= [C_{yy}^{(c)}]^{-1} C_{yx}^{(c)} [C_{xx}^{(c)}]^{-1} C_{xy}^{(c)}. \end{aligned} \quad (3b)$$

The goal of 2D CCA is to determine the four projection matrices W_{x_1}, W_{x_2} and W_{y_1}, W_{y_2}, which transform raw data into the space of variables $X^{(k)} \to U^{(k)}$ and $Y^{(k)} \to V^{(k)}$. This is achieved by solving the four eigenvalue problems:

$$S^{(total\ 1,r)} W_{x_1}^{(r)} = \Lambda_{x_1}^{(r)} W_{x_1}^{(r)}; \quad S^{(total\ 2,r)} W_{y_1}^{(r)} = \Lambda_{y_1}^{(r)} W_{y_1}^{(r)} \tag{4a}$$

$$S^{(total\ 1,c)} W_{x_2}^{(c)} = \Lambda_{x_2}^{(c)} W_{x_2}^{(c)}; \quad S^{(total\ 2,c)} W_{y_2}^{(c)} = \Lambda_{y_2}^{(c)} W_{y_2}^{(c)}, \tag{4b}$$

where: $\Lambda_{x_1}, \Lambda_{y_1}, \Lambda_{x_2}, \Lambda_{y_2}$ - the diagonal matrices of eigenvalues; W_{x_1}, W_{x_2} and W_{y_1}, W_{y_2} - the projection matrices. The transformation of raw data into a new space is implemented as two-dimensional Karhunen-Loeve transform (KLT) in the form of:

$$U^{(k)} = W_{x_1}^T \overline{X}^{(k)} W_{y_1}, \quad V^{(k)} = W_{x_2}^T \overline{Y}^{(k)} W_{y_2}, \tag{5}$$

$\forall k$, where $U^{(k)}, V^{(k)}$ - matrices representing the original images in the new feature space.

The main components are the ones that have the highest values. Basic variability of covariance matrices can be described by $d \ll K$ largest eigenvalues. The number of principal components for rows $\lambda_i^{(r)}$, $i = 1, 2, \ldots, d_1$ and columns $\lambda_i^{(c)}$, $i = 1, 2, \ldots, d_2$ may be estimated by any known method.

It should be noted that $d_1 \ll M$; $d_2 \ll N$ and $d_1 \neq d_2$ in general case. The lower limit of parameter d can be chosen experimentally at the stage of verification of the analysis.

For dimensionality reduction procedure (5) should be modified. To do this we choose d rows of matrices $W_{x_1}^T, W_{y_1}^T$ corresponding to d largest eigenvalues, and based on those we form the matrices of reduction F_{x_1} and F_{y_1}. We also choose d columns of matrices W_{x_2}, W_{y_2} corresponding to d largest eigenvalues, and based on those we form the matrices of reduction F_{x_2} and F_{y_2}. Then we perform the "truncated" two-dimensional Karhunen-Loeve transformation, which can be represented in the following form [3, 4] (the symbol "^" determines the difference of result from (5):

$$\hat{U}^{(k)} = F_{x_1} \overline{X}^{(k)} F_{x_2}, \quad \hat{V}^{(k)} = F_{y_1} \overline{Y}^{(k)} F_{y_2}, \quad \forall k. \tag{6}$$

The size of resulting matrices in (6) is equal to $d \times d$ or $d_1 \times d_2$. The resulting matrices of variables are defined as

$$\hat{U} = [\hat{U}^{(1)} \hat{U}^{(2)} \ldots \hat{U}^{(K)}], \quad \hat{V} = [\hat{V}^{(1)} \hat{V}^{(2)} \ldots \hat{V}^{(K)}] \ \forall k. \tag{7}$$

Their dimensions will be $d \times d \times K$ or $d_1 \times d_2 \times K$.

Image database for experiments

Consider the case when the original images do not belong to the same global class. An example of this is the images from the set «People and Dogs», containing portraits of dogs and their owners. Several sample images are shown in Fig. 1(*a*) [5]. Here each pair of images contains a portrait of a person, presumably dog owner, and a front view of his dog. The image base allows to experimentally test how our visual assessment of similarity of these portraits in their original form is comparable to the formal assessments of similarity in the original feature space and in the subspaces.

Comparison of images in the original feature space

If we consider pairs of images in Fig. 1(*a*), we can see a resemblance between an owner and his dog. This resemblance is determined by the same camera angle, similar form and color of person's and dog's hair, appropriate color and shades of person's clothing.

Let's calculate color brightness histogram for each image. Example of this histograms and mutual phase correlation between histograms for pair 1 shown on Fig. 1(*b*).

The peak of this correlation is greater than 0.75, with a relatively small values of its side, which indicates a high degree of similarity between the images in each pair. Maximum correlation (≈0.9) is reached for a pair number 1, whose images are the most expressive similarities. This means that the subjective and formal evaluation color factor indicate the existence of a similarity in the two images are semantically unrelated.

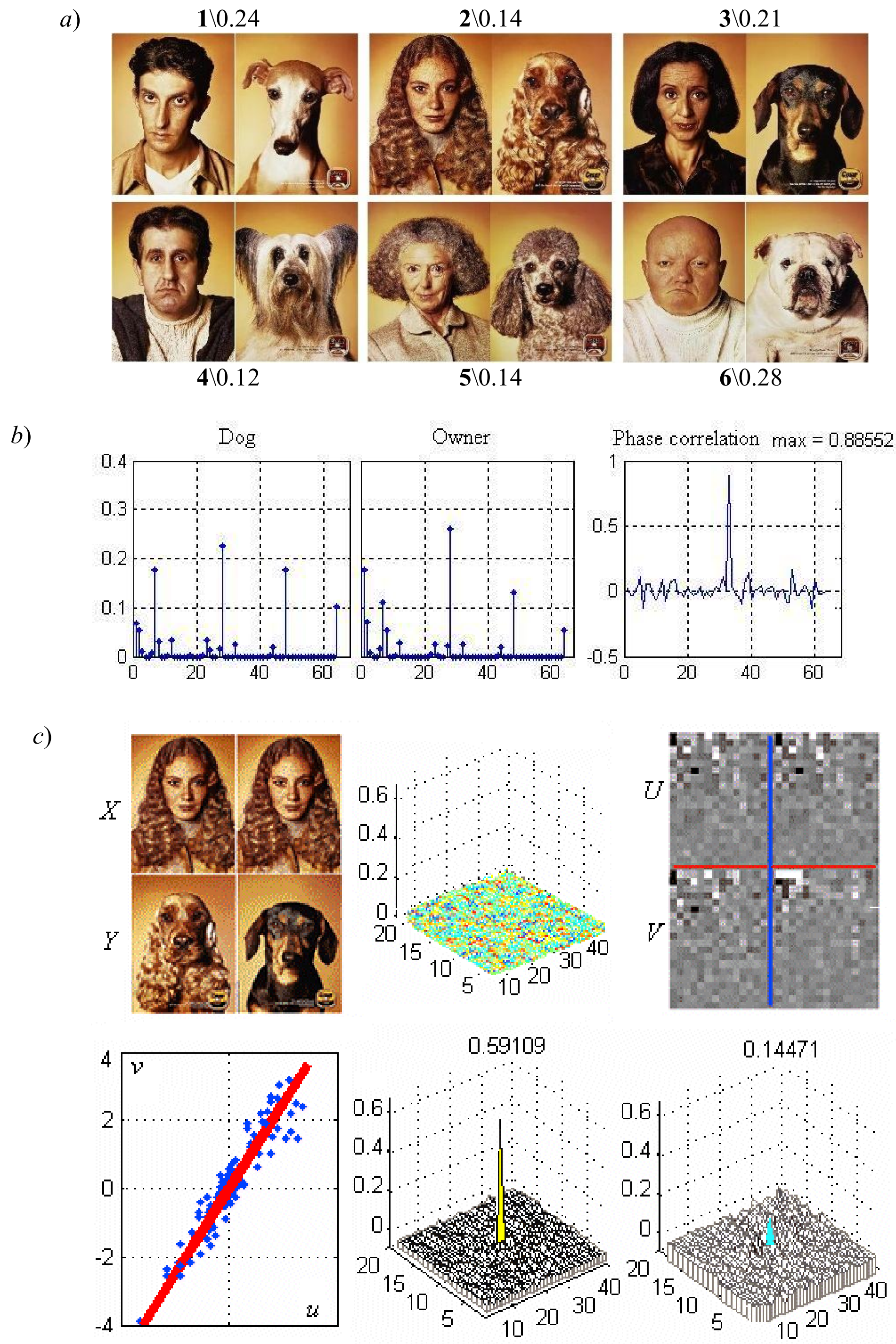

Fig. 1. Input data and processing result

Let's calculate mutual phase correlation between the image of an “owner” and a dog for a pair number 1. The top middle graph Fig. 1(*c*) show that the mutual phase correlation is almost zero. While it seems to us that the portraits are similar to each other, there is no actual correlation!

Let's compare their by means Structural SIMilarity Index (SSIM) [6]. The number of the pairs “owner-dog” and their SSIM value are shown in Fig. 1(*a*). Note that the values are quit low.

Representation of semantically different images in the space of canonical variables

Now let's check correlation between images "owner-dog" in the space of canonical variables.

Two pairs of source images are shown at left top Fig. 1(c), the canonical variables U and V, corresponding to the original images are shown at top right Fig. 1(c). It is easy to see that three of the four canonical variables contain the same values (luminance components) and, therefore, even look alike.

A graphical representation of the relationship between the variables in the new feature space for CCA, obtained by (7), is shown at left bottom Fig. 1(c). Note that canonical variables, shown as a function of U from V, have virtually linear relationship.

The phase correlation between the variables corresponding to the images from the same class is shown at bottom middle Fig. 1(c).

The phase correlation between the variables corresponding to the images from different classes is shown at bottom right Fig. 1(c).

From the results it is clear that in SCV between the variables U and V there was a correlation. This phase correlation between the variables from the same class is much higher value of 0.5 and significantly higher than the corresponding SSIM values. Correlation in the other case can be considered negligible, and the ratio of these correlations is 4 times.

High correlation of variables U and V in the space of canonical variables, their linear relationship to each other, "matching behavior" create prerequisites for mutual recognition and modelling of some variables from others. These tasks are easily implemented in the space of canonical variables.

Similar results were obtained for other pairs of source images, although we assumed that pairs of original images (owner-dog) belonged to semantically different global classes, and in fact their similarity has been proven only at the color level.

The main result of the analysis is as follows:

1) the fact of the correlation between the images of the dog and its owner in the space of canonical variables is confirmed, while any other ways could not confirm it;

2) indexing of images can be done using 2D CCA methods (search, recognition, model mapping of one image to another, reconstruction of images).

In general, this using example of developed algorithms 2D CCA/2D KLT has shown that they can be widely applied in recognition and classification of images, and also to decrease redundancy of image representation. The latter is due to the fact that selected value of parameter d << MN (MN is dimension of the original feature space).

Conclusion

The paper discussed the methods of presentation and comparison of semantically different images with assessment of their similarity in the original feature space, and presented the 2D CCA/2D KLT algorithm to implement the projection of these images and assessment of their similarity in the space of canonical variables.

To compare images in the original feature space we used their color histograms and phase correlation, two-dimensional phase correlation, and the structural similarity index. However, we could only partially prove similarity corresponding to subjective comparison of selected images.

It is shown that the «dissimilar» in the original feature space may be similar in the space of canonical variables. The projection in the space of canonical variables is implemented using 2D CCA/2D KLT presented in the paper and specifically designed to handle two sets of images. The results prove that 2D CCA/2D KLT methods can be widely used in search, pattern recognition and image classification tasks, and to decrease redundancy of images representation regardless of their semantic relationships.

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