https://doi.org/10.2352/ISSN.2470-1173.2018.16.COLOR-361

Assessing the useful of similarity measures for multispectral face recognition

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Abstract

The similarity analysis is a major issue in computer vision. This concept is denoted by a scalar which designates a distance measure giving the resemblance of two objects. Specifically, this distance is used in many areas such as image compression, image matching, biometrics, shape recognition, objects recognition, manufacturing industry, data analysis, etc. Several studies have shown that the choice of similarity measures depends on the type of data. This paper presents an evaluation of some similarity measures in the literature and a proposed similarity function taking into account image feature. The features concerned are textures and key-points. The data used in this study came from multispectral imaging by using visible and thermal infrared images.

Keywords: *multispectral imaging, face recognition, image fusion, visible and thermal infrared, similarity measures*

Introduction

The concept of similarity measure is transverse. It is a mathematical tool that is used in several sciences such as imaging, data analysis, physics, etc. Specifically, in computer vision, the distance concept is applied in several applications such as biometrics, objects recognition, manufacturing industry, quality control, content-based image retrieval, image quality assessment, medical imaging, etc.
Considering, the importance of this subject, many studies are interested in the distance concepts such as similarity and dissimilarity [13]. It has been proven in several studies that the choice and effectiveness of these metrics depends on the data type to manipulate.
In mathematics, a distance is defined as a length between two points. The similarity is a value used to quantify the resemblance of two objects in terms of common points. Also, the similarity measure gives the matches number while the dissimilarity measure gives the number of difference. Generally, similarity measures are classified into three groups which are geometric measures, measures of the information theory and statistical measures. A study of Sun-Hyuk Cha [15] presents a classification giving many families including the L_p family, L_1 family, intersection family, inner product family, squared-chord family (fidelity family), the χ_2 family (squared L_2 family, the shannon's entropy family, and others.
In general, similarity and dissimilarity measures used in computer vision are based on two methods. The first method concerns feature extraction such as shape, color, texture, key-point, etc. Then, the second method concerns images comparison by the use of image matching, similarity score, correlation etc. These two techniques are complementary. This paper focuses on the use of similarity score in multispectral face recognition wich is an emerging biometric method. For this purpose, several distances are used and evaluated.
As a goal, this study has a double contribution:

- A study of performance similarity measures including a proposed similarity function proposed in this study;
- An application of similarity score in multispectral face recognition using visible/thermal infrared images.

Theorical approach

This part first presents the theoretical aspects of metric distance, similarity and dissimilarity measures. Then, using five distance families, a description of distances is made.

Notion of distance, similarity and dissimilarity

The resemblance of two images I1 and I2 can be quoted by a value. This value can be a distance measure, a similarity measure or a dissimilarity measure. A distance denoted by dist on a set B is an application of BxB into R^+ satisfying the following axioms:

$$(P_1)\ \text{identity}\quad dist(I_1, I_2) = 0 \Leftrightarrow I_1 = I_2 \qquad (1)$$

$$(P_2)\ \text{symetry}\quad dist(I_1, I_2) = dist(I_2, I_1) \qquad (2)$$

$$(P_3)\ \text{triangle inequality}\quad dist(I_1, I_3) \leq dist(I_1, I_2) + dist(I_2, I_3) \qquad (3)$$

A dissimilarity denoted dissimil is an application of BxB into R^+ satisfying the following axioms:

$$(P_4)\quad dissimil(I_1, I_2) = 0 \Rightarrow I_1 = I_2 \qquad (4)$$

$$(P_5)\ \text{symetry}\quad dissimil(I_1, I_2) = dissimil(I_2, I_1) \qquad (5)$$

A similarity denoted simil is an application of BxB into R^+ verifying the following axioms:

$$(P_6)\quad simil(I_1, I_2) \geq simil(I_1, I_1) \qquad (6)$$

$$(P_7)\ \text{symetry}\quad simil(I_1, I_2) = simil(I_2, I_1) \qquad (7)$$

The concepts defined previously obey the following remarks:

- A high similarity measure indicates a strong resemblance of the images I2 and I1;
- A low dissimilarity measure indicates a strong resemblance of the images I2 and I1;

- A similarity measure denoted simil can be transformed into a dissimilarity measure denoted dissimil. This is formulated dissimil (I1, I2) = similmax - simil (I1, I2), where similmax designed a maximum similarity.

Similarity and dissimilarity measures

Consider two vectors X($x_1, x_2, \ldots, x_n$) and Y($y_1, y_2, \ldots, y_n$).

L_p Minkowski family

The distance of Minkowski family or usual distance is a metric on a normed vector space. The general form of this distance is given by the formula (8):

$$d_{mink} = \sqrt[p]{\sum_{i=1}^{n}|x_i - y_i|^p} \quad (8)$$

Several variants of this formula are obtained by varying the values of p. It is the Euclidean distance for p = 2, the Manahattan or City-Block distance for p = 1 and Chebishev distance for p = ∞. These distances are respectively given by the formulas (9), (10) and (11)

$$d_{eucl} = \sqrt{\sum_{i=1}^{n}|x_i - y_i|^2} \quad (9)$$

$$d_{mana} = \sum_{i=1}^{n}|x_i - y| \quad (10)$$

$$d_{cheb} = max_i|x_i - y_i| \quad (11)$$

L_1 family

The L1 family is very large and contains distances such as those of Sorensen, Gower, Lerentzian, Canberra, Soergel and Kuczynski. In this section, the distances of Kaczynski and Canberra given are respectively presented by the formulas (12) and (13).

$$d_{kulc} = \sum_{i=1}^{n} \frac{|x_i - y_i|}{\sum_{i=1}^{d} min(x_i, y_i)} \quad (12)$$

$$d_{canb} = \sum_{i=1}^{n} \frac{|x_i - y_i|}{x_i + y_i} \quad (13)$$

It is noted that these distances use the absolute value of the difference with variants.

Intersection family

There is a wide variety of distances in this family. It is based on two notions in computer vision. These are the probability density functions (PDF) and the histogram [11]. The intersection between two probability density functions is described by the formula (14).

$$d_{inte} = \sum_{i=1}^{n} \min(x_i, y_i) \quad (14)$$

Concerning the distance between histograms it is presented by the formula (15).

$$d_{histo}(X,Y) = \frac{\sum_{i=0}^{l-1} min(H_X(i), H_Y(i))}{\sum_{i=0}^{l-1} H_Y(i)} \quad (15)$$

where H_X and H_Y are two histograms.

Also, the Tanimoto distance is given by the formula (16).

$$d_{tani}(X,Y) = \frac{\sum_{i=1}^{n}(max(x_i, y_i) - min(x_i, y_i))}{\sum_{i=1}^{d} max(x_i, y_i)} \quad (16)$$

Inner product family

The inner product or scalar product is a scalar obtained by the formula (17).

$$d_{inne}(X, Y) = X \bullet Y = \sum_{i=n}^{n} x_i \ y_i \quad (17)$$

Several distances use the inner product to calculate the similarity score. This study uses the cosine and jaccard distances described respectively by the formulas (18) and (19).

$$d_{cosi}(X, Y) = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}} \quad (18)$$

The cosine distance is based on the computation of the angle between two vectors, it is simply an angular metric.

Squared-chord family (fidelity family)

The basic formula of the squared-chord is given by the formula (19)

$$d_{sqeu} = \sum_{i=1}^{d}(P_i - Q_i)^2 \quad (19)$$

The fidelity family contains the distances of Matusita, Fidelity and Battacharrya respectively presented by the formulas (20), (21) and (22).

$$d_{matu} = \sqrt{\sum_{i=1}^{n}\left(\sqrt{x_i} - \sqrt{y_i}\right)^2} \quad (20)$$

$$d_{batta} = -ln \sum_{i=1}^{d} \sqrt{x_i \, y_i} \quad (21)$$

$$d_{fide} = \sum_{i=1}^{n} \sqrt{x_i \, y_i} \quad (22)$$

Squared L_2 family (χ2 family)

This family is also called statistical family. The basic measure used is the square euclidean distance given by the formula (23).

$$d_{sqeu} = \sum_{i=1}^{n}(x_i - y_i)^2 \quad (23)$$

Several other distances are built from this distance such as the Pearson distance $\chi 2$ and the chi-square distance defined by the formulas (24) and (25).

$$d_{pea2}(P,Q) = \sum_{i=1}^{n} \frac{(x_i - y_i)^2}{y_i} \quad (24)$$

$$d_{chi2}(H_X, H_Y) = \sum_{i=0}^{l-1} \frac{(H_X(i) - m(i))^2}{m(i)} \quad (25)$$

where $m(i) = \frac{H_x(i) + H_y(i)}{2}$, H_x et H_y are two histograms.

Shannon's entropy family (divergent measure family)

In the probabilities and information theories, the divergence, also called the contrast function, is a function which gives the measure of two probability distributions by using statistical notions. The divergence may not be symmetrical and obey triangular inequality.

In theory, the Kullback-Leibler divergence, also called relative entropy, is a measure of dissimilarity between two distributions of probabilities X and Y. It considers histograms as distributions and gives dissimilarity by calculating relative entropy. The KL-divergence is described by the formula (26)

$$d_{kuLe}(X, Y) = \sum_{i=1}^{n} x_i \, ln\frac{x_i}{y_i} \quad (26)$$

The principle of Jeffrey Divergence consists in measuring the dissimilarity of two random variables in information theory. It is based on the notion of the average discriminant information between the two random signals. The Jeffrey divergence given by the formula

(27) has the advantage of being the symmetric version of the Kullback-Leibler divergence.

$$d_{jeff}(X, Y)=\sum_{i=1}^{n}(x_i - y_i)\ ln\frac{x_i}{y_i} \tag{27}$$

The Jensen-Shannon divergence called total divergence to the average measures the similarity between two probability distributions. The Kullback-Leibler divergence has the advantage of being symmetric and gives a finite value. The formula (28) describes the Jensen-Shannon divergence.

$$d_{jesh}(X, Y)=\frac{1}{2}\left(\sum_{i=1}^{n}(x_i - y_i)\ ln\frac{x_i}{y_i}\right) \tag{28}$$

In addition to the distances described above, this paper presents two other distances which are Mahalanobis distance and Earth Mover's Distance (EMD) distance.

The Mahalanobis distance gives the correlation between two series of measurements. It has the advantage of taking into account the variance and the correlation of the data series. This distance described in formula (29), measures the dissimilarity between two vectors of the same distribution.

$$d_{Maha}(X, Y)=\sqrt{(x-y)^T S^{-1}(x-y)} \tag{29}$$

where S is the covariance matrix and $(x\text{-}y)^T$ is the transpose of difference.

EMD distance can be used to compare two histograms to evaluate a similarity measure using optimization algorithm. This algorithm is used for optimal transport problems in operational research. In computer vision, this distance is the minimum energy required to transform one distribution into another. This method focuses on finding the minimum flow F by considering all transport dij to transform the histogram X into a Y histogram. This notion is presented in formula (30).

$$d_{EMD}(X, Y)= \min_{F}\sum_i\sum_j f_{ij}d_{ij} \tag{30}$$

The concepts of distance are described in literature with several applications [4].

The proposed method

Correlation and image fusion

Multispectral imaging improves the capacity and reliability of image interpretation. Image fusion allows to combine information from multiple images from different sources. Considering its success, the image fusion is used in many areas of computer vision including face recognition [6] [14]. This paper focuses on multispectral face recognition using visible and thermal infrared images.

For this purpose, the multispectral face recognition presents itself as an alternative to traditional face recognition by the use of visible and thermal infrared images [6].

For image fusion, pairs of visible and thermal infrared images are used. First, the calculation of entropy shows that the infrared images are richer in information than the visible images. The entropy formula is given by the formula (31).

$$He =-\sum_{i=0}^{L}h_{I_f}(i)log_2\, h_{I_f}(i) \tag{31}$$

Then, the correlation of the pairs of images was proved by the mutual information (MI) [17] [18] [19] giving the common information and the similarity measure of Sum of Squared Differences (SSD) to verify the similarity. These two notions are given in formulas (32) and (33).

$$MI = \sum_{i=1}^{M}\sum_{j=1}^{N}h_{I_r I_f}(i,j)log_2\left(\frac{h_{I_r I_f}(i,j)}{h_{I_r}(i,j)h_j(i,j)}\right) \tag{32}$$

$$SSD= \sum_{(i,jj)\in W}(I1(i,j) - I2(x+i, y+j))^2 \tag{33}$$

In the literature on image fusion, several methods exist and this study presents three fusion methods which are Principal Component Analysis (PCA), Multi-resolution Singular Value Decomposition and Average (AVG).

For image quality assessment, four different metric are used [1] [18]. These metrics are the Root mean Square Error (RMSE), the Percentage Fit Error (PFE), the Mean Absolute Error (MAE), the Peak Signal to Noise (PSNR).

The different metrics used, show that PCA fusion method [10] [16] give best image fusion with some results presented in Figure 1.

Figure 1. Set of images extracted from the database. Each line from top to bottom presents visible images, corresponding thermal infrared images, corresponding fused images by PCA fusion method.

Feature extraction

In the field of object recognition, feature extraction consists in quantifying the measurable properties in an image. In this study the features used are key-points and texture.

Concerning texture [2], statistical notions are used to estimate textures by the local measurement and the dispersion measure.

First the mean allows to make a local measurement. The average is obtained by the sum of all the components divided by the total number of components as indicated by the formula (34).

$$\bar{X}= \frac{1}{n}\sum_{i=1}^{n} x_i \tag{34}$$

For dispersion measure, the standard deviation and the variance are indicated. As for the variance, it measures the variable dispersion. And this is the square root of the variance. The variance and standard deviation are given by the formulas (35) and (36)

$$\text{var(X)}=\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{X})^2 \tag{35}$$

$$\text{std(X)}=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{X})^2} \tag{36}$$

Concerning texture characteristics, the skewness coefficient and the kurtosis coefficient are used. These two measures characterize the data set location and variability.

The skewness is a classic measure of asymmetry. The skewness value is used to interpret the spread distribution. The formula (37) presents the skewness.

$$\text{skewness(X)}=\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{X})^3}{s^3} \tag{37}$$

where $\bar{X}$ is the mean, s the standard deviation, n data number

Kurtosis (peakedness) is a flattening measure of a variable distribution. The formula (38) gives kurtosis which is a form parameter.

$$\text{kurtosis(x)}=\frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{X})^4}{s^4} \tag{38}$$

Where $\bar{X}$ is the mean, s the standard deviation, n data number

For feature extraction, interest points were also used. The key-point extraction, conventionally is based on three steps, which are the key-point detection, the key-point description and the images matching. One of the most famous detector is Scale invariant Feature Transform (SIFT) [3].

A study on a comparative study of descriptors and detectors in multispectral face recognition has shown the use of binary descriptors. The results of this study showed that there is a good compromise by using the Speed Up Robust Features (SURF) detector [5] and Fast Retina Key-point (FREAK) descriptor [12]. This justifies the use of SURF detector and the FREAK descriptor for key-point extraction [8] [9].

The signature of an image can be represented by a vector, a set of vectors, graphs, etc. In this experiment, for the signatures construction, we used the notion of vectors whose components are std, skweness, kurtosis, entropy, key-points respectively designating the standard deviation, the skewness, the kurtosis, the entropy and the key-points obtained by the SURF/FREAK method.

In addition, the features extracted are taken into account for the computation of similarity function denoted d $_{MSF}$, using the euclidean distance as shown in Table 1.

Table 1. Similarity function to compute the similarity score of two images X and Y.

Function distance = d $_{MSF}$ (X, Y)

x1 ← std(X)

x2 ← skweness(X)

x3 ← kurtosis(X)

x4 ← entropy(X)

x5 ← surffreak(X)

A= [x1, x2, x3, x4, x5]

y1 ← std(Y)

y2 ← skweness(Y)

y3 ← kurtosis(Y)

y4 ← entropy(Y)

y5 ← surffreak(Y)

B= [y1, y2, y3, y4, y5]

Distance ← $\sqrt{(x1-y1)^2+(x2-y2)^2+(x3-y3)^2+(x4-y4)^2+(x5-y5)^2}$

return (distance).

In the proposed method, features extracted are the texture and interest points. The combination of these two features better characterizes an image with the advantage of being robust and invariant. For this purpose, feature vectors and a similarity function based on Euclidean distance are built. Then, an image matching uses similarity calculation applying the similarity function, another distance, mutual information, image matching from the key points obtained and editing a similarity map. Finally, the results obtained make it possible to make decisions. This process can be recapitulated in Figure 2.

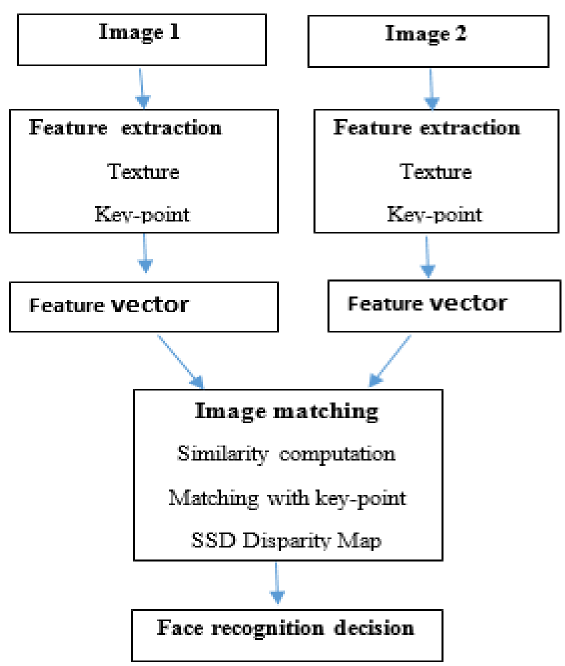

Figure 2. Diagram of the proposed face recognition method based on similarity score

Experimental results

Database

For experiments, a database is elaborated from IRIS (Imaging Robotics Intelligent System) database [7]. IRIS database contains visible and thermal infrared face images. This study uses facial images in visible and thermal infrared of 14 faces in four poses with three illuminations which are Lon (Left Light On), Off (Left and Right Off) and Ron (Right Light On). In all, image fusion of 336 pairs of facial images gives 168 fused images

Description of experience

In order to evaluate the multispectral face recognition methods under analysis, three kinds of experiments were carried out which are illumination variation, poses variation and the combination of poses and illuminations. The experiments are presented in the following.

Illuminations variation. In this experiment, for a given subject, a position is fixed and the illumination conditions which are Lon, Ron and Off are varied. The same experience is repeated for each direction.

Poses variation. In this experiment, for a given subject, an illumination is fixed and the four poses are varied. The same experience is repeated for each illumination.

Illuminations and poses variation. In this experiment taken into account the variation of subject, illumination and poses.

Results

For the experience, sixty cases were tested. A set of images is presented in figure 3. This set presents:

- a same subject with the same pose and illumination variation;
- a same subject with the same illumination and poses and poses variation;
- different subject with the same pose and the same illumination;
- different subject with the different poses and illumination variation.

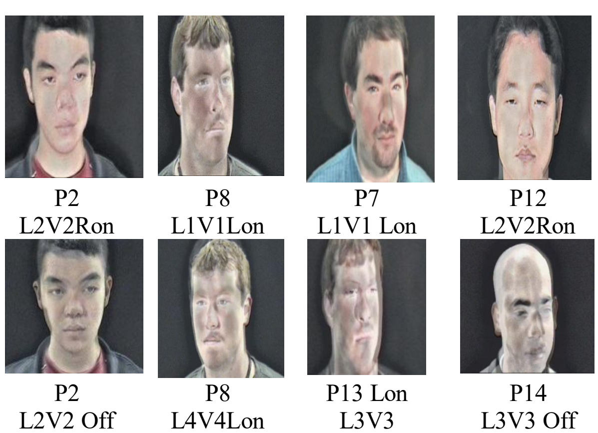

Figure 3. Set of images used for similarity score. Each line from top to bottom presents images and corresponding images used the computation of similarity score

The results obtained are presented below.

Table 2. Results of similarity score between images using distances described previously and the similarity function proposed.

Images / Distances	P2 L2V2 Ron P2 L2V2 Off	P8 L1V1 Lon P8 L4V4 Lon	P7 L1V1 Lon P8 L4V4 Ron	P12 L2V2 Ron P14 L3V3 Off
Euclidean	4.14	1.53	0.38	3.23
Manahattan	7.94	2.82	0.71	6.11
Chebishev	2.70	1.07	2.26	2.05
Kulzinski	54.21	17.72	3.45	70.27
Canberra	15.95	6.72	1.64	15.14
Intersection	6.03	8.59	9.64	6.94
histogram intersection	3.97	1.41	0.35	3.06
Tanimoto	22.72	11.04	3.13	20.84
Cosine	2.70	0.30	0.22	1.34
Matusita	9.02	0.97	0.41	3.70
Battacharrya	0.87	0.14	0.01	0.71
fidelity	9.16	9.87	9.99	9.32
Jeffrey divergence	1.65	0.27	0.02	1.32
Pearson chi2	6.91	0.92	0.07	11.36
Chi2	1.6	0.26	0.02	1.23
Kullback-leiber	3.86	0.50	0.03	3.26
Jensen-shanon	0.82	0.14	0.01	0.66
EMD	85.11	29.53	16.61	64.19
d_{MSF}	12.88	14.01	49.77	16.27

By observing Table 2, the fused images are the best candidates for face recognition. Therefore, similarity score is an efficient way of multispectral face recognition to improve traditional methods. The different tests and results confirm this assumption by the use of nineteen distances including the proposed distance. However, difficult environment conditions have an influence in face recognition.

Conclusion

The performance of multispectral face recognition compared to traditional face recognition is a major issue. This paper focuses on an assessing of similarity measure in multispectral face recognition using fused images visible and thermal infrared images. A distance can designate the resemblance of two images. This similarity can be robust by taking into account specific properties. All the distances presented are usable in the multispectral imaging but their quality varies in unconstraint environment such as illumination and poses. The proposed distance follows the same trend but has the advantage of using features like textures and key-points that give more precision.

Finally, as an extension of this work, emerging face recognition such as multispectral face recognition is interested in several aspects such as total darkness, disguises (makeups, hats, glasses, etc.), partial occlusion, variable distance, eye detection accuracy and facial expressions. In the future, we will work on different spectral images separately and even their combination.

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