Improved Isomap Algorithm for Motion Analysis

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Abstract

Euclidean distance, Hausdorff distance and SSP distance are discussed, and SSP distance is used to improve Isomap algorithm. Two methods are put forward for improving Isomap algorithm. One is aligning input data of original Isomap algorithm, the other is modifying Isomap algorithm itself. SSP distance is used to search neighbors and compose neighborhood graph, and the plot for each dimension of Isomap representation is used for visualization of Isomap representation. Motion analysis experiments results show that improved Isomap algorithm is better than original Isomap algorithm for translated data and has better visualization results of Isomap representation.

Keywords: Nonlinear dimensionality reduction, Isomap, Motion analysis

1. Introduction

Data analysis and visualization are very important for many areas of science and technology [1]. Finding compact representations of high-dimensional data is the fundamental problem of dimensionality reduction. The motivation of dimensionality reduction includes: reducing storage requirements, eliminating noise, extracting feature for recognition and projecting data to a low-dimensional space. Human brain representations the world through dealing with data from large numbers of sensory inputs. Coherent structure in the world leads to strong correlations between inputs, which will result in observations that lie on a smooth low-dimensional manifold. If the data can be represented as points in a high-dimensional vector space, it should inherently have a much more compact representation.

Dimensionality reduction method can be divided into two kinds: linear dimensionality reduction methods and nonlinear dimensionality reduction (NDR) methods. Linear dimensionality reduction methods include: PCA (principal component analysis), ICA (independent component analysis), LDA (linear discriminate analysis), LFA (local feature analysis), and so on. Nonlinear dimensionality reduction methods also can be categorized into two kinds: kernel-based methods and eigenvalue-based methods. Kernel-based methods include: KPCA (kernel principal component analysis), KICA (kernel independent component analysis), KDA (kernel discriminate analysis), and so on. Eigenvalue-based methods include: Isomap (Isometric Feature Mapping) [1], LLE (locally linear embedding) [2], Laplacian Eigenmap[3], and so on.

Isomap is an excellent NDR method [1]. Isomap uses approximate geodesic distance instead of Euclidean distance, and represents a set of images as a set of points in a low-dimensional space which is corresponding to natural parameterizations of the image set. Because there are similarities within adjacent frames of sequence, Isomap is very suitable to analyze moving pictures and videos.

Isomap is perfect in theory and can obtain good low-dimensional representation of man-made data and some practical data. Isomap can't always give good low-dimensional representation of practical data. Translation of data is usually appeared in practical data. The form of data translation depends on the type of data. For example, the translation of speech signal is lies on a horizontal line, and the translation of image signal is lies on an image plane. Isomap uses Euclidean distance to find neighbors and construct neighborhood graph, and Euclidean distance is not a good measurement for translated data. So an improved Isomap algorithm is needed. There will be two methods for improving Isomap algorithm. One is aligning properly input data of original Isomap algorithm to eliminate the influence of data translation, the other is modifying Isomap algorithm itself.

The rest part of this paper is arranged as follows. Similarity measurement will be discussed in section 2. Improved Isomap algorithm is depicted in section 3. Motion analysis experiments and results are in section 4. Section 5 is conclusion.

2. Similarity measurement

Usually Euclidean distance is used for finding K-nearest neighbors and construct neighborhood graph in the first step of Isomap algorithm [1]. Translation of data is one of the commonest phenomena, and Euclidean distance is unsuitable for translated data.

2.1. Euclidean distance

The definition of Euclidean distance between two vector $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ is:

$$D_E = \left\| \boldsymbol{x}_i - \boldsymbol{x}_j \right\|_2 = \sqrt{\sum_{n=1}^{D} \left(\boldsymbol{x}_i(n) - \boldsymbol{x}_j(n) \right)^2} \qquad (1)$$

Figure 1(a) is the original silhouette of gait image. Figure 1(b) is the horizontal translation versions of figure 1(a). Figure 1(c) is the Euclidean distance between original image and its horizontal translation versions. Figure 1 shows, directed Euclidean distance between two images is not a good distance measurement.

Figure 2(a) is another original silhouette of gait image for same person. Figure 2(b) is the horizontal translation versions of figure 2(a). Figure 2(c) is the Euclidean distance between horizontal translation versions of figure 2(a) and figure 1(a). Figure 2(c) shows, the minimum Euclidean distance is obtained when the horizontal shift is 1 pixel. Figure 2 also shows, directed Euclidean distance between two images is not a good distance measurement.

2.2. Hausdorff distance

Hausdorff distance is a kind of distance measurement between two point sets [4]. Let $\boldsymbol{A} = \{\boldsymbol{a}_1, \boldsymbol{a}_2, ..., \boldsymbol{a}_m\}$ and $\boldsymbol{B} = \{\boldsymbol{b}_1, \boldsymbol{b}_2, ..., \boldsymbol{b}_n\}$ denote two finite point sets. The definition of Hausdorff distance is

$$H(\boldsymbol{A}, \boldsymbol{B}) = \max(h(\boldsymbol{A}, \boldsymbol{B}), h(\boldsymbol{B}, \boldsymbol{A})) \qquad (2)$$

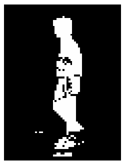
$h(\boldsymbol{A}, \boldsymbol{B})$ is the directed Hausdorff distance, and it is defined as

$$h(\boldsymbol{A}, \boldsymbol{B}) = \max_{\boldsymbol{a} \in \boldsymbol{A}} \min_{\boldsymbol{b} \in \boldsymbol{B}} \left\| \boldsymbol{a} - \boldsymbol{b} \right\|_2 \qquad (3)$$

Hausdorff distance is useful for shape matching. Hausdorff distance eliminates the influence of point translation to some extent.

2.3. SSP distance

BenAbdelkader directly models human motion, and believes the dynamic feature of gait is encoded in pair-wise image similarities of gait images, and gives the definition of self-similarity plot (SSP) [5]. The definition of SSP is



(a)

(b)

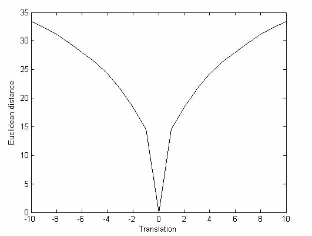


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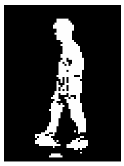
Fig. 1: (a) Original image, (b) Horizontal translation versions of original image, (c) Euclidean distance between original image and its horizontal translation versions.



(a)

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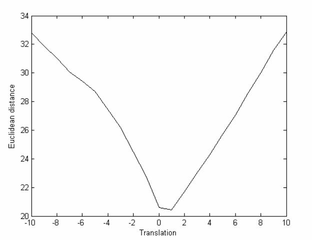

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Fig. 2: (a) Original image, (b) Horizontal translation versions of original image, (c) Euclidean distance between original image in figure 1(a) and horizontal translation versions of original image in figure 2(a).

$$S = \min_{|dx,dy|<r} \sum_{(x,y)\in \boldsymbol{B}_{t_1}} \left| \boldsymbol{O}_{t_1}(x+dx, y+dy) - \boldsymbol{O}_{t_2}(x,y) \right| \quad (4)$$

where, t_1 and t_2 are numbers of silhouette images, $\boldsymbol{B}_{t_1}$ is the bounding box of silhouette image t_1, r is a small search radius, and $\boldsymbol{O}_{t_1}$ and $\boldsymbol{O}_{t_2}$ are silhouette images. When SSP is used for gait alignment, we let $t_2 = 1$ and $\boldsymbol{f}_{t_1}$ is aligned with dx and dy. The definition of SSP distance between two vectors $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ is

$$D_S(\boldsymbol{x}_i, \boldsymbol{x}_j) = \min(D_E(\boldsymbol{x}_i, T(\boldsymbol{x}_j))) \quad (5)$$

where $T(\boldsymbol{x}_j)$ is the translation version of $\boldsymbol{x}_j$. The operator T is depends on the type of data. SSP distance removes the influence of data translation to a great extent.

3. Improved isomap algorithm

Two methods can be used for improving Isomap algorithm. One is aligning input data of original Isomap algorithm, the other is modifying original Isomap algorithm itself.

3.1. Aligning input data of isomap algorithm

For linear or nonlinear dimensionality reduction methods, data alignment is a very important step. The input of Isomap algorithm is matrix $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_N\}$, where $\boldsymbol{x}_i \in R^D$. The alignment version of $\boldsymbol{X}$ is

$$T_S(\boldsymbol{X}) = \{T_S(\boldsymbol{x}_1), T_S(\boldsymbol{x}_2), ..., T_S(\boldsymbol{x}_N)\} \quad (6)$$

$T_S(\boldsymbol{x}_i)$ satisfies

$$D_E(T_S(\boldsymbol{x}_i), \boldsymbol{x}_R) = D_S(\boldsymbol{x}_i, \boldsymbol{x}_R) \quad (7)$$

$\boldsymbol{x}_R$ is a reference vector, and it may be $\boldsymbol{x}_R = \boldsymbol{x}_1$. A more sophisticated $\boldsymbol{x}_R$ is needed.

3.2. Improved isomap algorithm

Improved Isomap algorithm includes following four steps:

- Constructing neighborhood graph. According to SSP distance, for each point, its neighbor points are K -nearest neighbors or points within a radius r.
- Computing shortest paths using Dijkstra's algorithm or Folyd's algorithm.
- Constructing low dimensional embedding using MDS (multidimensional scaling).
- Visualization of lower-dimensional Isomap representation. Classical method for visualization of low-dimensional embedding is the plot of 1D, 2D or 3D Isomap representations. Another available method is the plot for each dimension of low-dimensional Isomap representation.

4. Motion analysis experiments and results

Gait images come from CMU MOBO database [6]. CMU MOBO database has 25 persons, 6 visual angles and 4 kinds of walk: slow walk, fast walk, slow incline walk and slow walk with a ball.

4.1. The comparison of improved and original isomap algorithm

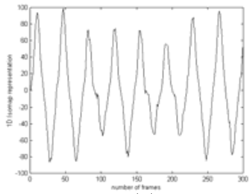
Figure 3(a) is the 1D Isomap representation of gait sequence using original Isomap algorithm. Figure 3(b) is the 1D Isomap representation of gait sequence using original Isomap algorithm with input data alignment. Figure 3(c) is the 1D Isomap representation of gait sequence using improved Isomap algorithm. Figure 3 shows, original Isomap algorithm can not give good 1D Isomap representation, and input data alignment or improved Isomap algorithm has similar good 1D Isomap representation.

Figure 4(a) is the 1D Isomap representation of gait sequence using original Isomap algorithm. Figure 4(b) is the 1D Isomap representation of gait sequence using original Isomap algorithm with input data alignment. Figure 4(c) is the 1D Isomap representation of gait sequence using improved Isomap algorithm. Figure 4 shows, only improved Isomap algorithm can have good 1D Isomap representation.

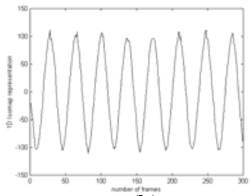
Experiments results show, input data alignment based Isomap algorithm is better than original Isomap algorithm, and improved Isomap algorithm is better than input data alignment based Isomap algorithm.

4.2. Visualization of low-dimensional isomap representation

Figure 5(a) is the plot for 1D Isomap representation of gait sequence using improved Isomap algorithm, figure 5(b) is the plot for 2D Isomap representation of gait sequence using improved Isomap algorithm, and figure 5(c) is the plot for 3D Isomap representation of gait sequence using improved Isomap algorithm. Figure 5(a) shows, zero-crossing, local maximum and local minimum of 1D LLE representation represents



(a)



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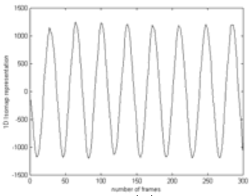

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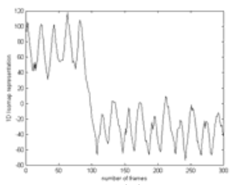
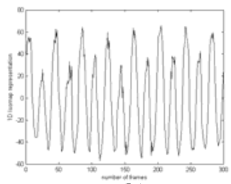
Fig. 3: 1D Isomap representation of gait sequence using original Isomap algorithm, input data alignment and improved Isomap algorithm respectively.



(a)



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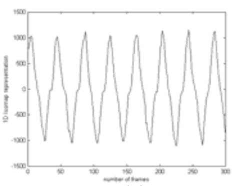


(c)

Fig. 4: 1D Isomap representation of gait sequence using original Isomap algorithm, input data alignment and improved Isomap algorithm respectively.

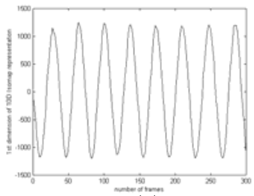
gait cycle respectively, and the shape of 1D Isomap representation represents space extension of gait [7]. Figure 5(b) and figure 5(c) show, 2D and 3D Isomap representation also represent gait cycle and dynamic features of gait, and have more useful information for gait analysis and recognition.

Figure 6(a) is the first dimension of Isomap representation using improved Isomap algorithm, figure 6(b) is the third dimension of Isomap representation using improved Isomap algorithm, and figure 6(c) is the fifth dimension of Isomap representation using improved Isomap algorithm. Figure 6 shows, different dimension of Isomap representation represents different dynamic feature of gait in different scale. The smaller dimension of Isomap representation shows dynamic features of gait in lager scale, the larger dimension of Isomap representation shows dynamic features of gait in smaller scale.

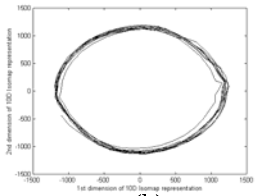
5. Conclusions

Improved Isomap algorithm is brought out. Generally there is shift in practical data. The form of shift depends on the type of data. Data alignment and registration is a very important step for linear or nonlinear dimensionality reduction methods. Original Isomap algorithm uses Euclidean distance to find neighbors and construct neighborhood graph, and Euclidean distance is not a good measurement for translated data. Euclidean distance and Hausdorff distance are discussed, and the definition of SSP distance is given and is used for improved Isomap algorithm. Two methods are put forward to improve Isomap algorithm. One is aligning input data of original Isomap algorithm, the other is modifying Isomap algorithm itself. In improved Isomap algorithm, SSP distance is used to seek neighbors and make up neighborhood graph, and the plot for each dimension of Isomap representation is used for visualization of Isomap representation. Motion Analysis experiments results show, improved Isomap algorithm is better than original Isomap algorithm for translation data and gains better visualization results of Isomap representation.

In further work, improved Isomap algorithm will be used for gait analysis and recognition, gesture analysis and recognition, satellite cloud image analysis and recognition, video analysis, and so on. Because LLE algorithm is still not robust for data translation just as Isomap algorithm, improved LLE algorithm is needed.



(a)



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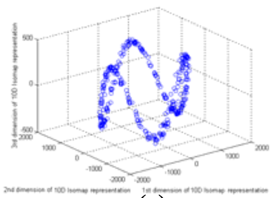
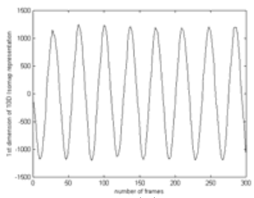
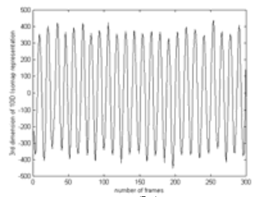


(c)

Fig. 5: 1D, 2D and 3D Isomap representation of gait sequence using improved Isomap algorithm.



(a)



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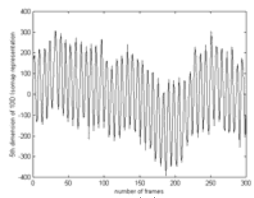

(c)

Fig. 6: The first, third and fifth dimensions of Isomap representation for gait sequence using improved Isomap algorithm.

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