A Robust Identification Approach to Gait Recognition

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Abstract

In this paper we address the problem of human gait recognition from a robust identification and model (in)validation prospective. The main idea is to apply dimensionality reduction technique to extract the spatio-temporal information by mapping the gait silhouette sequence to a low dimensional time sequence, which is considered as the output of a linear time invariant (LTI) system. A class of gaits is associated to a nominal discrete LTI system which has a periodic impulse response and is identified by robust identification approach. Correspondingly, gait recognition can be formulated as measuring the difference between the models representing different gait sequences. Our approach provides an efficient way to extract, to model shape-motion information of gait sequence, and to measure the difference between gait sequence models which is robust to gait cycle localization, gross appearance variation, and time scaling. These results are illustrated with practical examples on popular gait databases.

1. Introduction

Biometrics involves human's physiological or behavioral characteristics to identify a person automatically. Gait recognition refers to human identification from a longer distance than other biometrics like face, iris and fingerprint. From this point of view, gait recognition is more attractive than other biometric approaches.

The problem of gait recognition has received considerable attention within the Computer Vision community. Existing approaches to this problem can be divided into different types: those primarily seek to exploit context information and those rely more on modeling human gait and recasting activity recognition as a classification problem (see [1], [8], [14] and references therein). Modeling human gait has been extensively researched leading to different approaches, such as bio-mechanical motivated modeling [4] and input-output box modeling [13]. According to the use of motion and shape information, there are two different types of gait recognition algorithms. Those methods focusing on motion information use body part moments, eigengait space, and Hidden Markov models (HMM) [17, 2, 9]. Although these approaches have proven successful in many scenarios, being lack of shape information, in other scenarios they perform worse than the methods using mainly shape information [16, 21].

However, shape information based approaches perform poorly when significant gross shape variation exists. To improve the robustness of these approaches, shape and motion information are applied jointly, such as self similarity plots [3]. Frieze patterns are proposed by Liu *et al.* [12] as another spatiotemporal pattern. To deal with the problem that Frieze patterns are sensitive to shape variation, this approach has been extended by Lee [10] to shape variance-based frieze patterns. Although experiments show the approaches involving both shape and motion information achieve a better performance than using shape or motion information alone, they suffer from other problems, *e.g.* computational burden from computing difference between image pairs and noise introduced by key frames selection.

In order to circumvent these difficulties, in this paper we propose a method for robust gait recognition based upon modeling shape variation information extracted by Locale Linear Embedding (LLE) and recasting the recognition problem into a robust model (in)validation form. A general, simple, and efficient comprehensive mechanism is achieved for gait recognition bypassing the problems of gait cycle localization, key frames selection, being sensitive to gross shape variation, and computational burden from image difference calculation. The proposed method has the following advantages over currently existing techniques:

1. It leads to a non–iterative, computationally attractive algorithm that extracts spatio-temporal information from gait silhouette sequences.

2. It applies a robust identification approach to spatio-temporal information modeling, which is a great help to deal with noise from the various sources, *e.g.* pattern cycle localization and key frame selection.

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3. It recasts the recognition problem to a model (in)validation problem, and provides a way measuring difference of gait sequences, which is robust to gross shape changes, gait cycle localization, and time scaling.

These results are illustrated with examples on CMU MoBo database, a well known dataset for gait recognition performance analysis.

2. Spatio-Temporal Information Extraction

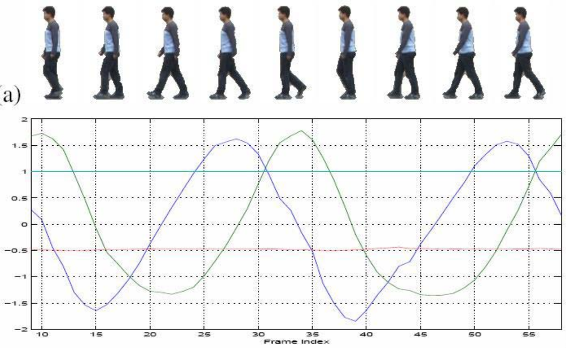
Shape and motion information are used together by many techniques to improve the robustness of gait recognition. These spatio-temporal information are extracted from the image sequence through a variety of ways. Some approaches use image features, such as angular displacement of body parts *et al*. [13]. Some refer to context information, such as image differences and self similarity cues *et al*. Shape variation-based frieze patterns are proposed by Lee *et al*. [10] as a representation for gaits that capture the intra and inter-shape variations. However, these techniques are faced with several difficulties: being fragile to appearance, being difficult to extract information, and computational burden. To deal with these problems, motivated by results in video inpainting [5], we propose a spatio-temporal gait information extraction method based on nonlinear dimensionality reduction (NDR). In this paper, we apply LLE to accomplish the information extraction.

2.1. Locally Linear Embedding

In this section we provide a brief description of a NDR method, LLE, that preserves local neighborhoods [20]. This method has been successfully used to model and learn human appearance changes in [7, 11]. Given T frames of a sequence, denote by z_t the vector obtained by stacking the pixels of the target at frame t. The goal is to associate to each vector z_t a point y_t in a lower dimensional manifold, e.g. $\dim(y_t) \ll \dim(z_t)$, while preserving the local structure. With this property, LLE is capable to extract the shape variation information.

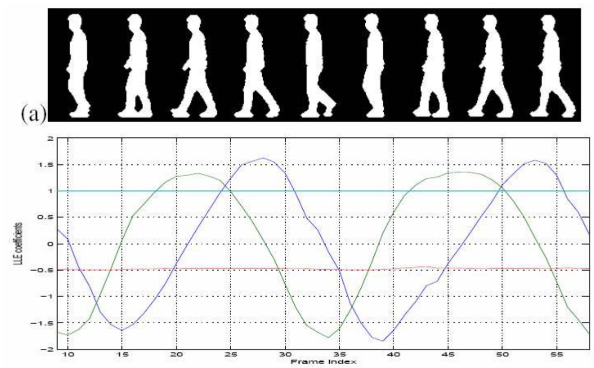
Hwasup [11] and Ding [5] have demonstrated that LLE is capable to map high dimensional image sequence to low dimensional manifold (LLE space) and to extract the spatio-temporal variation information. Correspondingly, the gait sequence are projected to a LLE space while the shape and motion information are extracted into the LLE sequence. It has been shown that these information are valuable to dynamics modeling. In our paper, we will use this LLE sequence to represent a gait sequence and further accomplish the gait recognition.

Example 1: Gait sequence to LLE space. Consider the gait sequence of frame 9-58. Original gait and projected LLE sequences are shown in Figure 1. Silhouette image and LLE sequence are in Figure 2. It can be concluded that spatio-temporal information extraction is not affected by using silhouette images.

(a)


(b)

Figure 1. Original gait sequence and LLE sequence. (a) Image frame 9, 14, 19, 24, 29, 34, 39, 44, and 49. (b) Corresponding LLE sequence.

(a)


(b)

Figure 2. Silhouette gait sequence and LLE sequence. (a) Silhouette frame 9, 14, 19, 24, 29, 34, 39, 44, and 49. (b) Corresponding LLE sequence.

2.2. Consistency problem of LLE

One important thing to be mentioned is the consistency of different gait sequences after LLE process. There is no doubt LLE can bring a consistent result intra a sequence. However, applying LLE on different parts of same long sequence separately will bring inconsistent results. This observation can be shown in Figure 3, where applying LLE on frame 107-156 brings different result from applying LLE on frame 1-156 as a whole. It is impossible to compare two LLE sequences with an inconsistent base. To deal with this problem, when comparing two gait sequences, we apply LLE on the set containing both sequences, which is stacking the two gait sequences together and applying LLE on the new sequence. This process not only accomplishes the data reduction and information extraction, but also assures the consistence of two LLE sequences.

Example 2: Consistency problem of LLE. Consider gait sequence frame 107-156 from the same set of **Exam-**

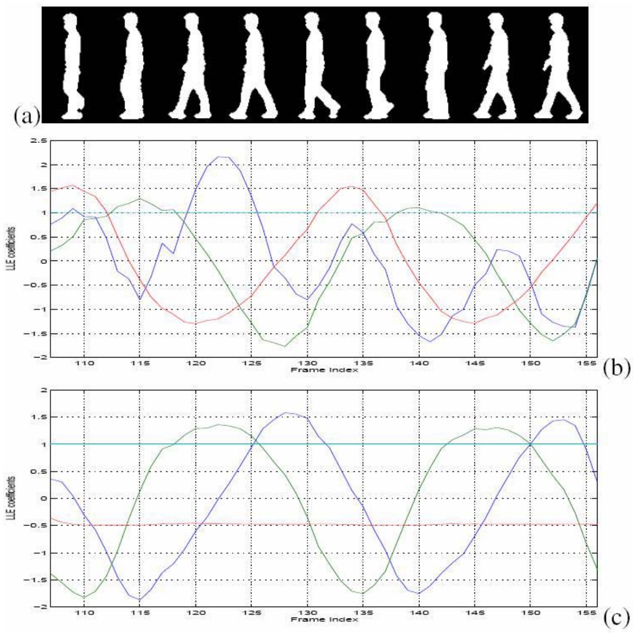


Figure 3. Silhouette gait sequence and LLE sequence. (a) Silhouette frame 107, 112, 117, 122, 127, 132, 137, 142, and 147. (b) LLE result using frame 107-156 only. (c) LLE result using both frame 9-58 and 107-156.

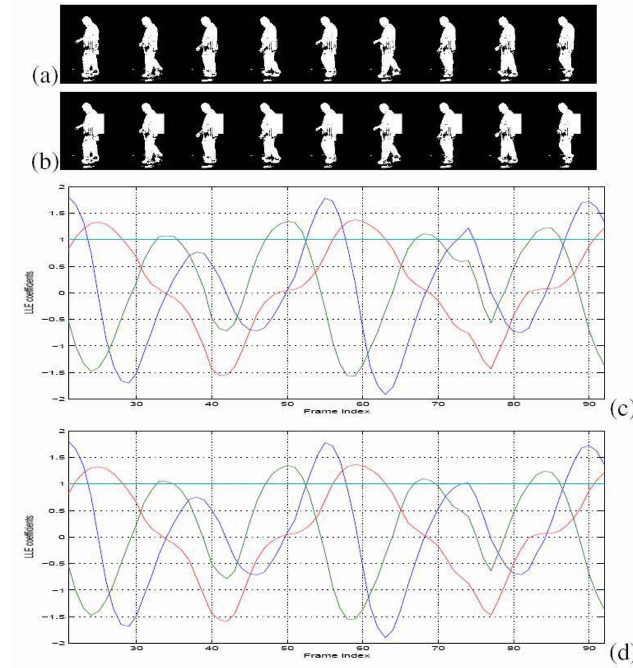


Figure 4. Silhouette gait sequence and LLE sequence. (a,b): silhouette frame 21, 29, 37, 45, 53, 61, 69, 77, and 85 from two sequence. (c,d): LLE sequence 21-92 of (a) and (b) respectively.

ple 1. Define S={silhouette frame 9-58 and 107-156}, S_1={silhouette frame 9-58}, and S_2={silhouette frame 107-156}. The LLE results are shown in Figure 3 (b) and (c), where (c) sequence 107-156 via LLE on S is consistent with Figure 2 (b), while (b) sequence 107-156 via LLE on S_2 is obviously not consistent with LLE sequence 9-58 via LLE on S_1 as in Figure 2 (b).

2.3. Robustness to gross appearance variation

Shape is one key factor to influence the gait recognition performance. Several approaches are proven to be fragile to changes of the shape. Take CMU MoBo database as an example. When the appearance difference between person 'slow walk' and 'ball walk' is significant, the recognition rate decreases a lot. To make the algorithm robust to this variation, several algorithms have been proposed such as shape variation frieze pattern *et al*. [10]. However these algorithms introduce other problems as mentioned previously.

In contrast to other approaches, our LLE based information extraction is robust to gross appearance variation. This is mainly because of the inherence data clustering mechanism, where key information are extracted while appearance variation is omitted as the noise.

Example 3: Robustness to gross appearance variation. This is an artificial example simulating gross changes in body shape by adding a square block on the body. The LLE coefficients in Figure 4 (c) and (d) are almost identical even though the silhouette sequence (a) and (b) are significantly different, showing that the key information has been extracted and is not influenced by the noise from the gross appearance variation.

3. Robust Identification of Gait Sequences

In this section, we introduce the system modeling of finite-dimensional, discrete-time, linear shift invariant (FDLSI) systems. Robust identification of linear time invariant (LTI) systems that have a periodic impulse response arises in the context of many practical problems, such as texture imaging, sensor networks *et al*.

3.1. General dynamics model

Consider the LLE sequence corresponding to the t^{th} gait frame expressed in a vector $\mathbf{y}_t$ and assume that these values are generated by a stationary Gauss–Markov random process. This is equivalent to assuming that $\mathbf{y}_t$ is related to its values in previous frames by an ARMAX model of the form:

$$\mathbf{y}_t = \sum_{i=0}^{m-1} g_i \mathbf{y}_{t-i} + \sum_{i=0}^{m-1} h_i \mathbf{u}_{t-i} \quad (1)$$

where g_i, h_i are fixed coefficients and $\mathbf{u}(.)$ denotes a stochastic input. Note that this can be always assumed without loss of generality, since given N_F measurements of $\mathbf{y}(.), \mathbf{u}(.)$, there always exists a linear operator such that

(1) is satisfied ([15], Chapter 10). Finally, by absorbing if necessary the spectral density of $\mathbf{u}$ in the coefficients g_i and h_i, it can always be assumed that $\mathbf{u}(.)$ is an impulse. This system can be represented using a state space model given by the equations:

$$\begin{cases} x_{t+1} &= Ax_t + Bu_t \\ y_t &= Cx_t + Du_t \end{cases} \tag{2}$$

where $A \in R^{m\times m}$, $B \in R^{m\times 1}$, $C \in R^{1\times m}$ and $D \in R$ are constant matrices. It will be assumed that this system is both controllable and observable, i.e., it is a minimum realization.

Generally, gait sequences have a near periodic property, which can be considered as the output of a FDLSI system.

3.2. Robust identification of FDLSI system

A robust identification algorithm to FDLSI system is introduced by Sznaier and Camps [18] and is extended by Ding *et al*. [6] to 2-Dimensional cases. A LTI system with a periodic impulse response has great applications in texture image processing, sensor network, etc. For the gait recognition problem, we can consider each gait LLE sequence as the output of a FDLSI model and apply robust identification to model it.

Consider a FDLSI system represented by 2, a Hank matrix is constructed as follows:

$$H_y^n \doteq \begin{bmatrix} y_1 & y_2 & \cdots & y_n \\ y_2 & y_3 & \cdots & y_{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_n & y_{n+1} & \cdots & y_{2n-1} \end{bmatrix} \tag{3}$$

The main idea is to address the robust identification by working directly with the constructed Hankel matrix: (a) Construct Hankel matrix H_y^n, (b) Apply the singular value decomposition (SVD) on H_y^n to extract major components where noise constrains are satisfied, (c) Use major components to construct the identified FDLSI model. Since the impulse response is periodic, the Hankel matrix of the system under consideration is circulant and structural properties can then be exploited to obtain balanced realizations in an efficient way. Please refer to [18] for details.

4. Model (In)Validation

Model (in)validation of LTI systems in a Robust Control setting has been extensively addressed in the past decade. The problem of semi-blind frequency-domain (in)validation of discrete-time, LTI models can be formally stated as follows [18]:

Given (i) a priori information consisting of a candidate model, and set descriptions $\mathcal{N}$, Δ and $\mathcal{U}$ of the measurement noise, model uncertainty and experimental inputs, and

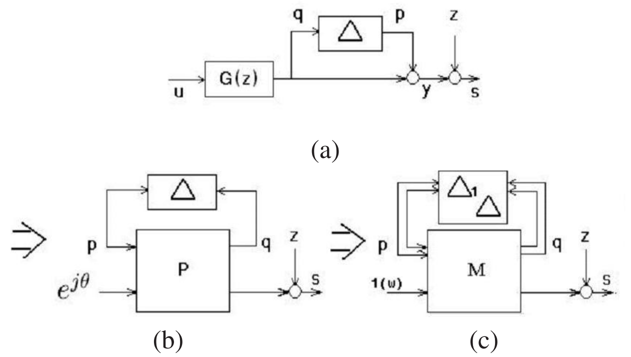


Figure 5. Semi-blind model (in)validation framework set-up and problems conversion. (a) General set-up for classification. (b) Semi-blind model (in)validation form. (c) Practical convex relaxation.

(ii) experimental data consisting of frequency-domain measurements, corrupted by additive noise, to an unknown input in $\mathcal{U}$, find whether the *a posteriori* experimental data is consistent with the *a priori* information, that is whether admissible uncertainty, input and noise could have generated this data.

4.1. Semi-blind model (in)validation

Semi-blind model (in)validation means the (in)validation of plants subject to unknown time delays or when the only information available about the input is its spectral power density. Semi-blind model (in)validation set-up is shown in Figure 5, where $G(z)$ denotes a nominal model, q and z denote the outputs of nominal model and the real observation data, Δ denotes the uncertainty between q and s, and z denotes the measurement noise in Figure 5 (a). Figure 5 (b) is a realization of upper linear fractional form of (a), where $e^{j\theta}$ denotes the unknown time delay of the input u. (c) is a convex relaxation to deal with (generically NP-hard) Bilinear Matrix Inequality minimization problem caused by $e^{j\theta}$. Please refer to [19] for more details.

Under the proposed framework in Figure 5, considering the observation data s as the data of another object, Figure 5 (a) is converted to an object recognition set-up. Then we can apply model (in)validation theorem to the problem set-up for the object recognition. The problem is formed as follows [19]:

• Find for $G(z)$ an input u, $|u(e^{j\omega})|$=1 and an admissible uncertainty operator Δ of minimum size γ_{opt}:

$$\gamma_{opt} \doteq \min_{\Delta,u} \{||\Delta||_* : s = [(\Delta + I)Gu] + z\}$$

where $||.||_*$ denotes some norm of interest.

• Consider γ_{opt} as the criteria for object classification, where the small γ_{opt} means the small mismatch, and vice versa.

Based on the above discussion, gait recognition problem can be transformed to a model (in)validation form. Here q

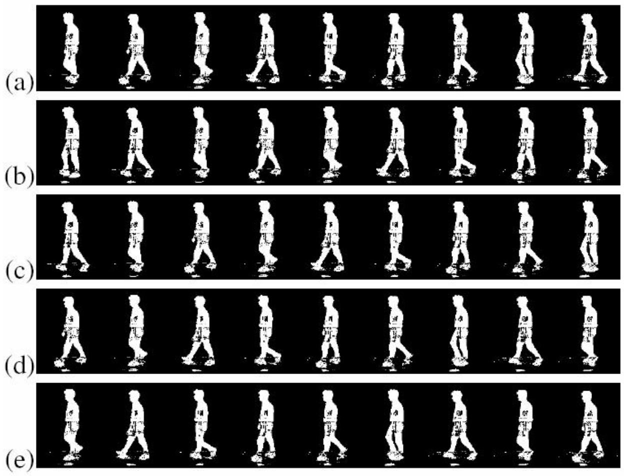


Figure 6. Different gait cycle in one silhouette sequence. (a) Silhouette frame 21, 29, 37, 45, 53, 61, 69, 77, and 85. (b) Silhouette frame 5, 13, 21, 29, 37, 45, 53, 61, and 69. (c) Silhouette frame 13, 21, 29, 37, 45, 53, 61, 69, and 77. (d) Silhouette frame 29, 37, 45, 53, 61, 69, 77, 85, and 93.

Table 1. γ_{opt} between different sequences in Figure 6 (a)-(e).

i	$\gamma_{opt}(i,b)$	$\gamma_{opt}(i,c)$	$\gamma_{opt}(i,d)$	$\gamma_{opt}(i,e)$
a	0.043	0.078	0.039	0.094

denotes the gait sequences from the nominal model representing the gallery sequence, and s denotes the probe gait sequence. Hence the $\gamma_{opt}(q,s)$ measures the difference between q and s. One input parameter is the noise level, where we choose this setting $||z||_2 < 0.1||q||_2$.

4.2. Robustness to gait cycle localization

The semi-blind (in)validation framework assures that the time delay of the q will not affect the recognition result, which means for gait sequence there is no need for cycle localization. Hence, this approach is robust to gait cycle localization.

Example 4: Robustness to gait cycle localization. Consider five gait sequence (a)-(e) in Figure 6. In this example, (a)-(e) are chosen from one long sequence and is consistent to each other. Apply previous robust identification and model (in)validation approach to do the gait recognition. The small values of γ_{opt} in Table 1 show these sequences are in one group, and demonstrate the robustness of our approach to gait cycle localization.

4.3. Robustness to time scaling

From robust modeling approach, we identify the models of LLE sequences which can help to improve the robustness to cases of motion changes. The idea is: when the motion of the person changes, the corresponding LLE sequence shows a time scaling result. With the model we identified, we can easily do time scaling on LLE sequence and handel the motion variations. Suppose LLE sequence $q(t)$ and $s(t)$ are from gallery set and probe set respectively, then $\gamma_{opt}(q,s)$ should be reformed as the follows, considering the time scaling factor α:

$$\gamma_{opt}(q,s) = \min \gamma_{opt}(q(t), s(\alpha t)) \quad \text{subject to } \alpha \in \hat{\alpha} \tag{4}$$

where $\hat{\alpha}$ denotes the set containing all possible α.

Example 5: Robustness to time scaling. Consider 'slow walk' and 'fast walk' silhouette sequence of the same person in Figure 7 (a) and (b). We can see in Figure 7 (c) and (d), the two LLE sequences are different because of the time scaling factor α. Considering this factor, the $\gamma_{opt}(\alpha)$ is plotted in Figure 8, and the results are shown in Table 2. It is shown that $\gamma_{opt}(1.2)$ gets minimized, which means $a(1.2t)$ is the sequence of best match to $b(t)$. With the consideration of time scaling factor, our method is more robust in the cases of motion variations.

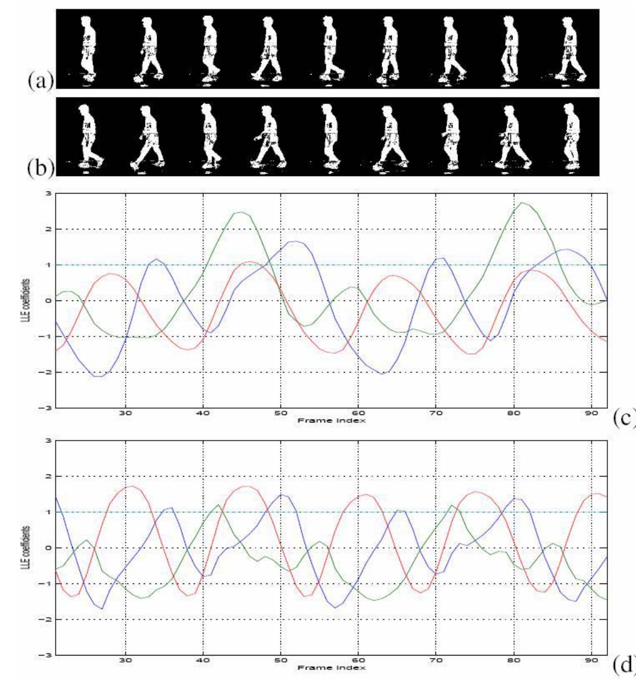


Figure 7. Silhouette gait sequence and LLE sequence. (a,b): silhouette frame 21, 29, 37, 45, 53, 61, 69, 77, and 85 from two sequence. (c,d): LLE sequence 21-92 of (a) and (b) respectively.

Table 2. γ_{opt} between different sequence in Figure 7 (a)-(b) for different scalling factor α.

i	$\gamma_{opt}(i,b)$						
	α=0.8	α=0.9	α=1.0	α=1.1	α=1.2	α=1.3	α=1.4
(a)	1.00	0.99	0.97	0.83	0.42	0.70	0.89

Example 6: Gait recognition between different se-

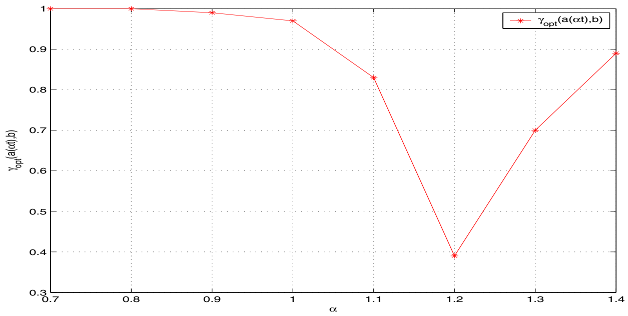


Figure 8. $\gamma_{opt}(a(\alpha t), b)$ with respect to α.

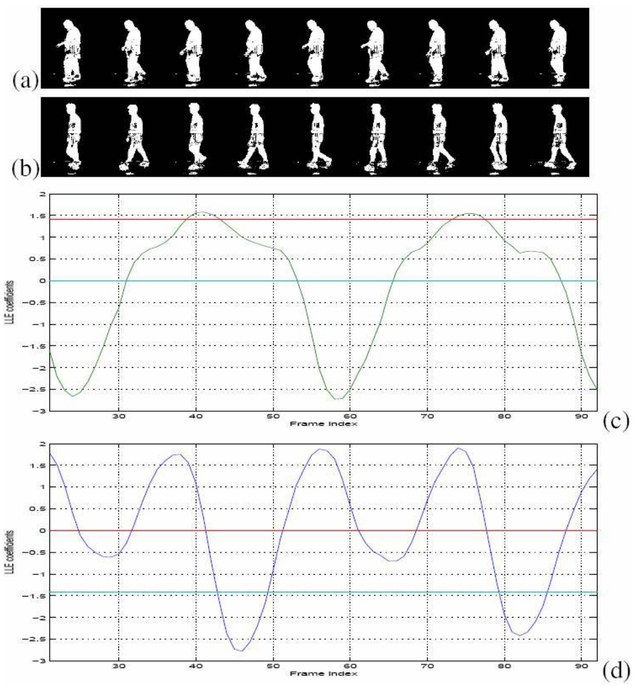


Figure 9. Silhouette gait sequence and LLE sequence. (a,b): silhouette frame 21, 29, 37, 45, 53, 61, 69, 77, and 85 from two sequence. (c,d): LLE sequence 21-92 of (a) and (b) respectively.

quences. This example considers two 'slow walking' sequences from different sets (persons) as Figure 9 (a) and (b). The corresponding LLE sequences are shown in Figure 9 (c) and (d), and $\gamma_{opt} = 0.97$ means the two sequence are dramatically different. Another one considers 'slow walk' and 'ball walk' sequence of the same person shown in Figure 10. The gross shape variation is significant, however $\gamma_{opt} = 0.32$ can easily classify these two sequences into one group. **Example 6** demonstrates the robustness of our algorithm.

4.4. Gait recognition

In this section, we summarize our approach into several steps as shown in Figure 11. For simplicity, we assume the probe input lp is a sequence with integer gait cycles, all

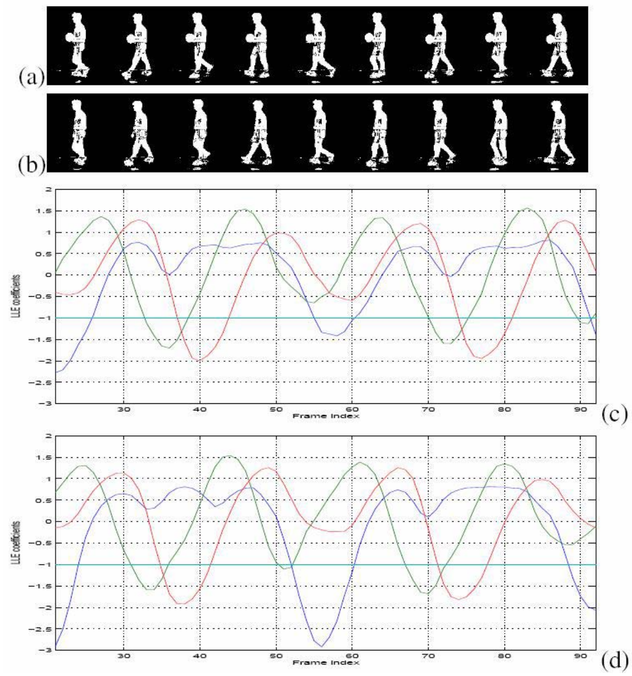


Figure 10. Silhouette gait sequence and LLE sequence. (a,b): silhouette frame 21, 29, 37, 45, 53, 61, 69, 77, and 85 from two sequence. (c,d): LLE sequence 21-92 of (a) and (b) respectively.

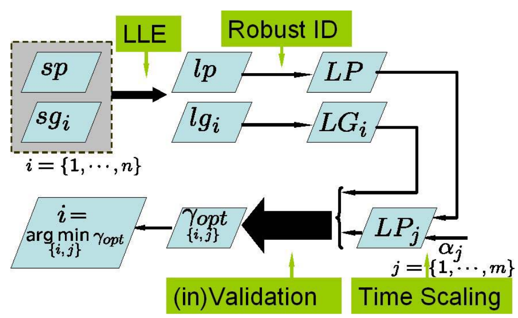


Figure 11. A general model for gait recognition.

the sequences are alighted by the center of mass, and all the gait sequences are the same side foot-forward. These assumptions are without loss of generality, because we can easily extract integer cycles of a gait sequence by observing the width variation information [10] or observing the peak of the LLE sequence. Moreover we can deal with different side foot-forward sequence by just considering $\alpha = -1$. The details of our approach are described in **Algorithm 1**.

Table 3. Test results by different recognition algorithms on CMU MoBo (*: Data are from [10]).

	CMU [16]	UMD [21]	MIT [9]	Frieze* [12]	SSP [3]	SVB* [10]	RIB
S/S	100%	100%	100%	100%	100%	100%	100%
F/F	-	100%	-	100%	100%	100%	100%
B/B	-	100%	-	100%	-	100%	100%
S/F	73%	77%	70%	100%	54%	82%	89%
F/S	-	86%	-	84%	39%	80%	88%
S/B	90%	48%	50%	81%	-	77%	93%
B/S	-	60%	-	50%	-	89%	94%
F/B	-	44%	-	50%	-	61%	77%
B/F	-	49%	-	50%	-	73%	79%

Algoritm 1: Robust Identification Based Gait Recognition

Input: Gallery silhouette sequence set $\{sg_i(t), i = 1, \cdots, n\}$, probe silhouette sequence $sp(t)$, time scaling factor set $\{\alpha_j, j = 1, \cdots, m\}$.
Output: Recognition result i^*.

1. For each i, apply LLE on $\{sp, sg_i\}$ to get $\{lp, lg_i\}$.
2. Obtain FDLSI model $\{LP(z), LG_i(z)\}$ via Robust Identification algorithm on $\{lp, lg_i\}$.
3. For each j, apply time scaling factor α_j on $LP(z)$ to get model $LP_j(z)$.
4. For each i, j, apply (in)validation algorithm on $\{LP_j, LG_i\}$ to calculate $\gamma_{opt}(i, j)$.
5. $i^* = \arg\min \gamma_{opt}(i, j)$ subject to i, j.

5. Experiments

To test our algorithm we do some extensive experiments. The gallery sequence and probe sequence are different in different cases.

5.1. CMU MoBo database

In this part we apply our proposed approach on the popular CMU MoBo database, where 25 subjects are recorded from 6 viewing angles and each of subject have four gait types (slow walk, fast walk, ball walk, inclined walk). For simplicity, we only consider the side view sequences for our experiments. Table 3 lists the recognition results by 7 different algorithms on CMU MoBo databases. It is shown that robust identification based (RIB) algorithm shows great improvement in the case of gross shape changes.

5.2. Examples of same person with different appearance

Similar to the example in [10], we generated a group of artificial sequences on CMU MoBo database as in Figure 12, where (b) is gallery sequence, (c1)-(c8) are probe sequences. The recognition results are shown in Table 4, where our proposed RIB algorithm performs more robustly than SVB.

(b) (c1) (c2) (c3) (c4) (c5) (c6) (c7) (c8)

Figure 12. Sample frame from probe b and c.

Table 4. Test results.

	c1	c2	c3	c4	c5	c6	c7	c8
Rate(%)-SVB	95	89	83	80	76	74	71	71
Rate(%)-RIB	100	95	94	94	90	90	91	89

6. Conclusion and Further Research

In this paper we addressed the problem of gait recognition using LLE, robust identification of FDLSI systems, and semi-blind model (in)validation. In order to solve this problem, we introduced algorithms for (i) mapping silhouette image sequence to LLE space to extract spatio-temporal information, (ii) identifying the FDLSI model from the spatio-temporal information, (iii) measuring the difference between two models scaled by given time scaling factors using semi-blind model (in)validation approach, and (iv) accomplishing the best matching pair according to the minimal $\gamma_{opt}(i, j)$ value. The underlying idea in all cases is that spatio-temporal information of a gait sequence can be extracted by LLE and modeled as shape variation can be modeled by a FDLSI system and the recognition problem can be converted into a model (in)validation problem. The effectiveness of this technique was illustrated using several examples on CMU MoBo databases.

These results point out to the central role that control theory can play in developing a comprehensive framework leading to a robust gait recognition algorithm. Our further research will focus on more examples for persons with different appearances and practical applications in real time environment.

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