Review on Vision-Based Gait Recognition Representations Classification Schemes and Datasets

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摘要

文章主要总结了步态特征提取、分类模式和标准步态数据库三个方面。有两种主要的最先进的方式：基于模型的（对人体模型化）和非基于模型（不需要对人体建模）的。

介绍

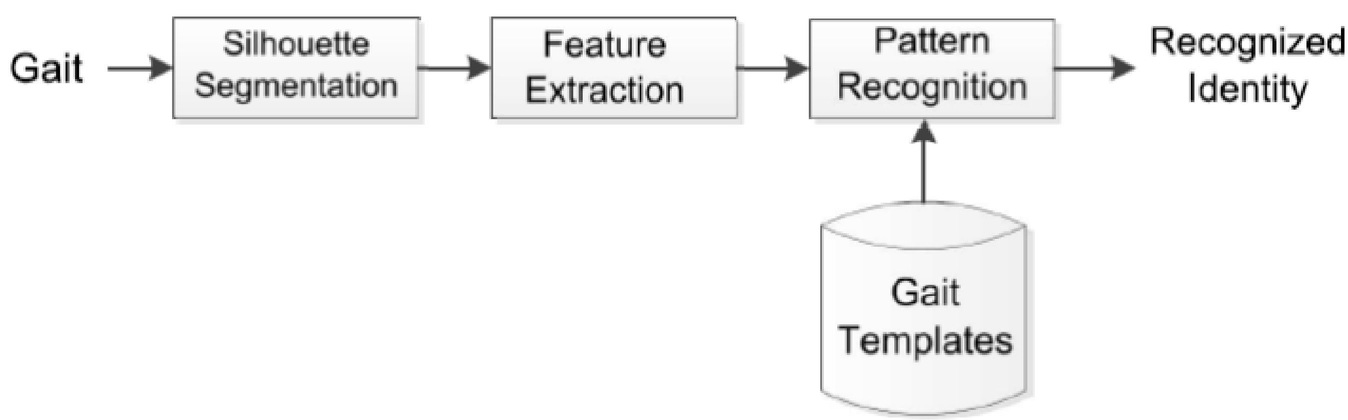

Fig. 1. The framework of vision-based gait recognition

基于视觉的步态识别算法基本框架

剪影提取

主要使用背景剪除法

特征提取

基于模型的和基于非模型的

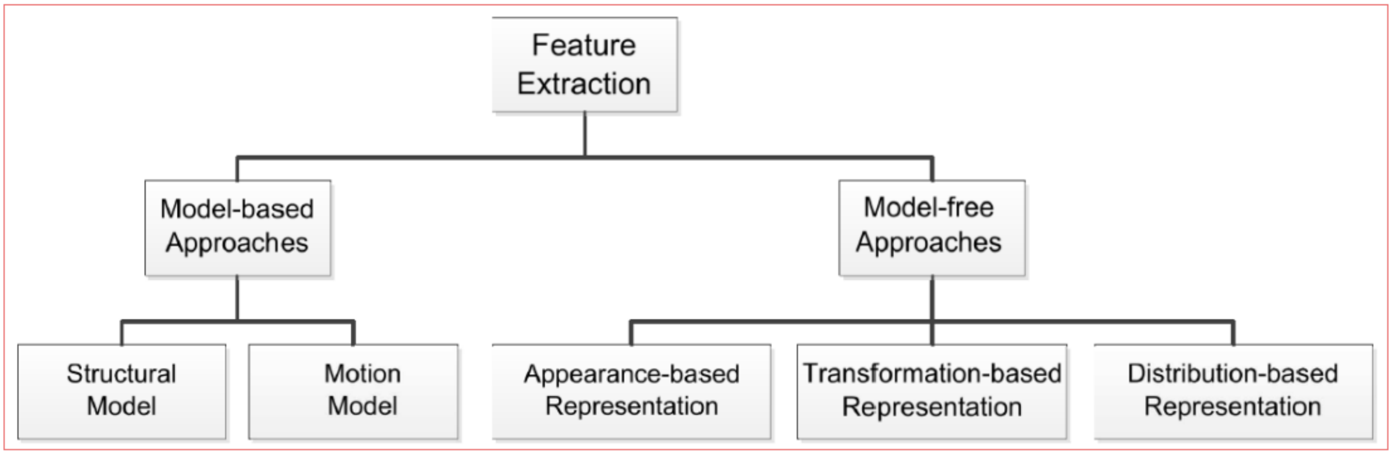

Fig. 2. The categorization of feature extraction schemes

Model-Based Approaches

使用人体成分或运动的模型参数（例如运动轨迹，肢体长度，肢体角速度等）来描述步行模式两种常用的步态表示是结构模型(Structural Model)和运动模型(Motion Model)

Structural Model

对人体各部位使用直线、骨架、椭圆等建立模型

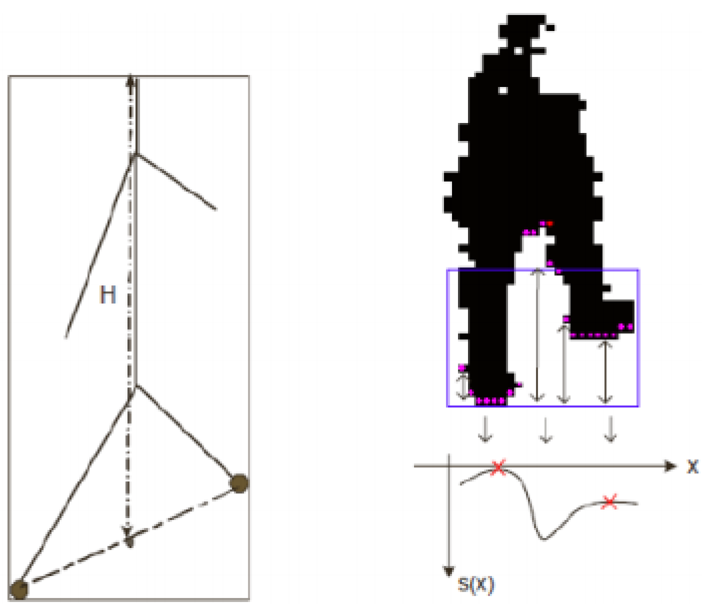

Fig. 3. The stick figure model in BenAbdelkader *et al*. (2002)

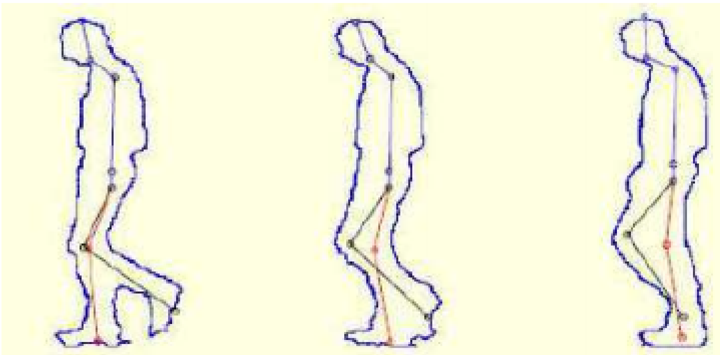

Fig. 4. The stick figure model in Yoo and Nixon (2011)

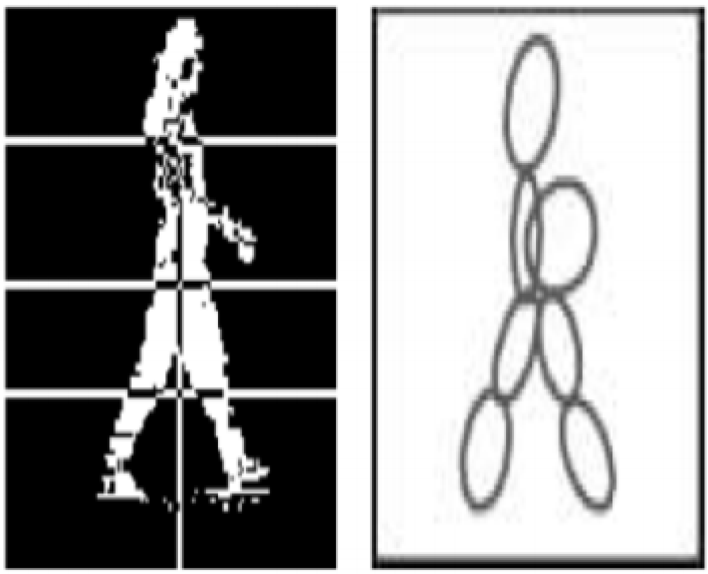

Fig. 5. The ellipsoidal model in Lee and Grimson (2002)

In a later work, Fathima and Banu (2012) performed

Fig. 6. The articulated model in Wagg and Nixon (2004)

Motion Model

Table 1. Summary of model-based approaches (structural model)

Literature	Gait features	Classifier/Distance metric
Bobick and Johnson (2001)	Static body parameters	Population covariance
BenAbdelkader *et al*. (2002)	Stick Fig. (stride and height parameters)	Bayesian classifier
Zhang *et al*. (2004)	Five-link biped (linked feature trajectories)	HMMs
Yoo and Nixon (2011)	Stick Fig.	kNN
Lee and Grimson (2002)	Ellipsoidal model (moment-based features)	kNN + Mahalanobis distance
Wagg and Nixon (2004)	Articulated model	kNN + Euclidean distance
Huang and Boulgouris (2009)	8 body components (geometry features)	Euclidean distance
Tafazzoli and Safabakhsh (2010)	3 body regions (posterior model of motion)	kNN

Table 2. Summary of model-based approaches (motion model)

Literature	Gait features	Classifier/distance metric
Cunado *et al*. (1997; 2003)	Pendulum (inclination of legs)	kNN
Yam *et al*. (2004)	Pendulum (joint angle trajectories)	kNN + Euclidean distance
Tanawongsuwan and Bobick (2001)	Joint angle trajectories	DTW
Yoo *et al*. (2002)	Joint angle trajectories	Neural networks
Wang *et al*. (2004)	Joint angle trajectories	kNN + Euclidean distance
Fathima and Banu (2012)	Joint angle trajectories	SVM
Lu *et al*. (2014)	Joint angle trajectories	SVM

Model-Free Approaches

直接从步态图像中抽取特征，主要分为：基于外表(appearance-based)、基于转换(transformation-based)、基于分布(disteribution-based)三种描述。

Appearance-Based Representation

步态的运动被计算为能量图，能量值高的区域运动越频繁。

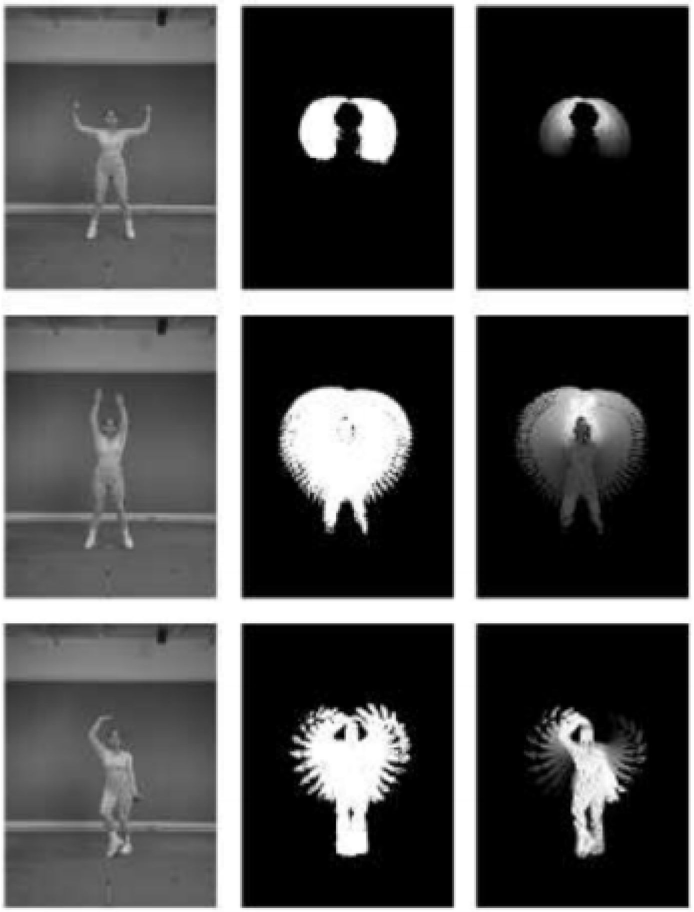

Fig. 7. The first column shows a sample frame of the actions. The second and third columns show their corresponding MEIs and MHIs (Bobick and Davis, 2001)

MHI的问题在于当出现自遮挡的时候，就很难描述运动方向。

2014年有人提出一个时间平均运动历史图像(TAMHI)，他们将步态周期分为几个规则的时间窗口，以生成复合图像，以更好地保存瞬态信息。然后用HOG特征算子计算步态特征。

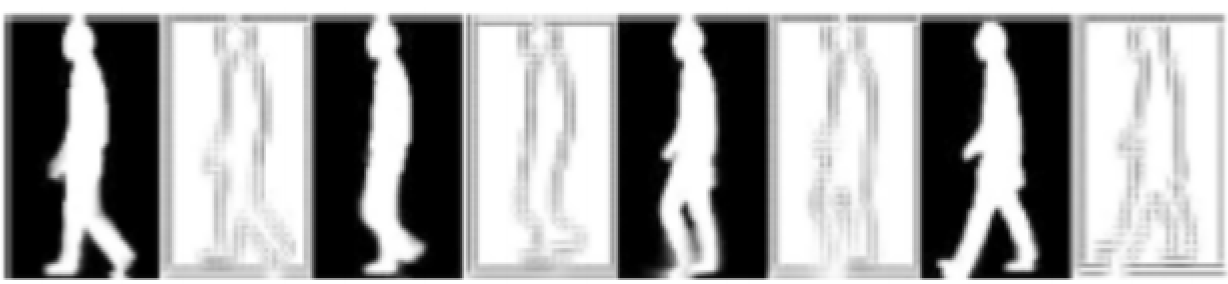

Fig. 8. Samples of the TAMHI composite images (odd columns) and the corresponding TAMHI-HOG descriptors (even columns) (Lee *et al*., 2014b)

接下来Liu和Sarkar（2004）提出了一种平均轮廓法，将耦合子空间分析（Coupled Subspace Analysis CSA）作为去除噪声的预处理步骤，并应用带有张量表示的判别分析（ Discriminant Analysis with Tensor Representation DATER）来增强判别能力

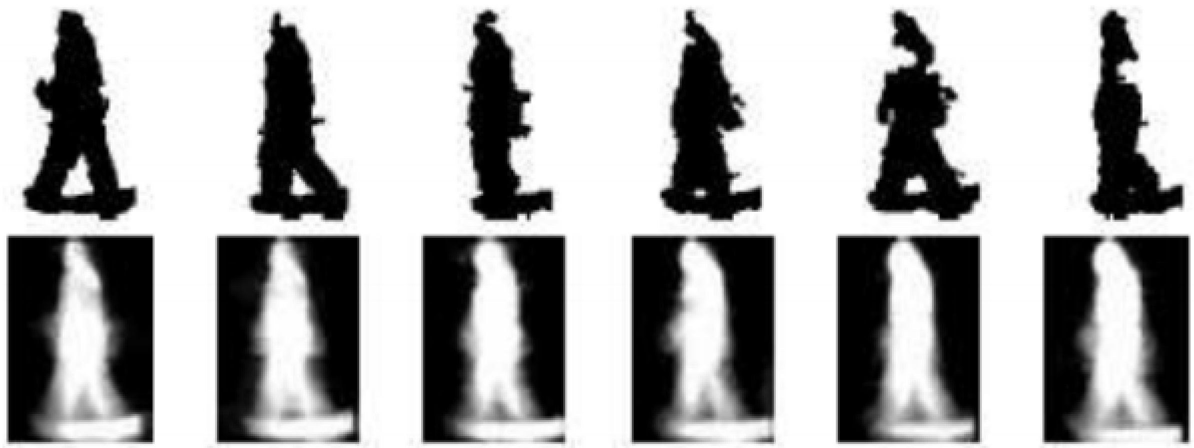

Fig. 9. The first row shows samples of the binary silhouettes over one gait cycle. The second row shows the averaged silhouettes for the subject; each averaged over a different gait cycle (Liu and Sarkar, 2004)

类似于平均轮廓法，Han and Bhanu (2006)提出了步态能量图（Gait Energy Image GEI）

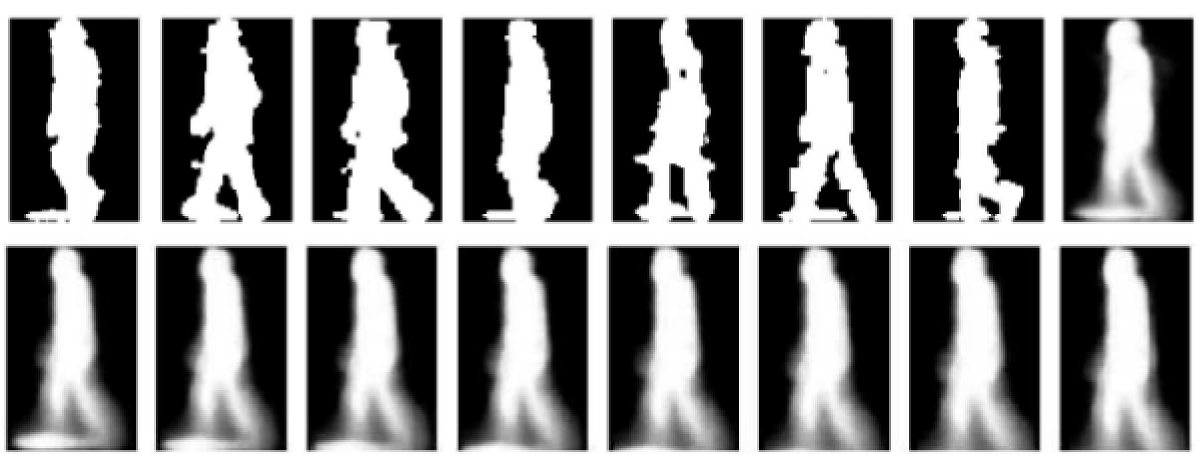

Fig. 10. First row shows the samples of normalized and aligned silhouettes. The rightmost image is the corresponding real GEI template. Second row shows the synthetic GEI templates generated by cropping the bottom portion of the real template and normalizing it to the original template size (Han and Bhanu, 2006)

Yang et al. (2008)构建了动态权重蒙版(dynamics weight mask)以增强动态区域与其他区域之间的对比度，提出了EGEI(Enhance GEI)

Zhang et al. (2009)提出对GEI的动态部分单独提取出来DGEI(Dynamic Gait Energy Image)，然后使用主成分分析降维再使用局部性投影。

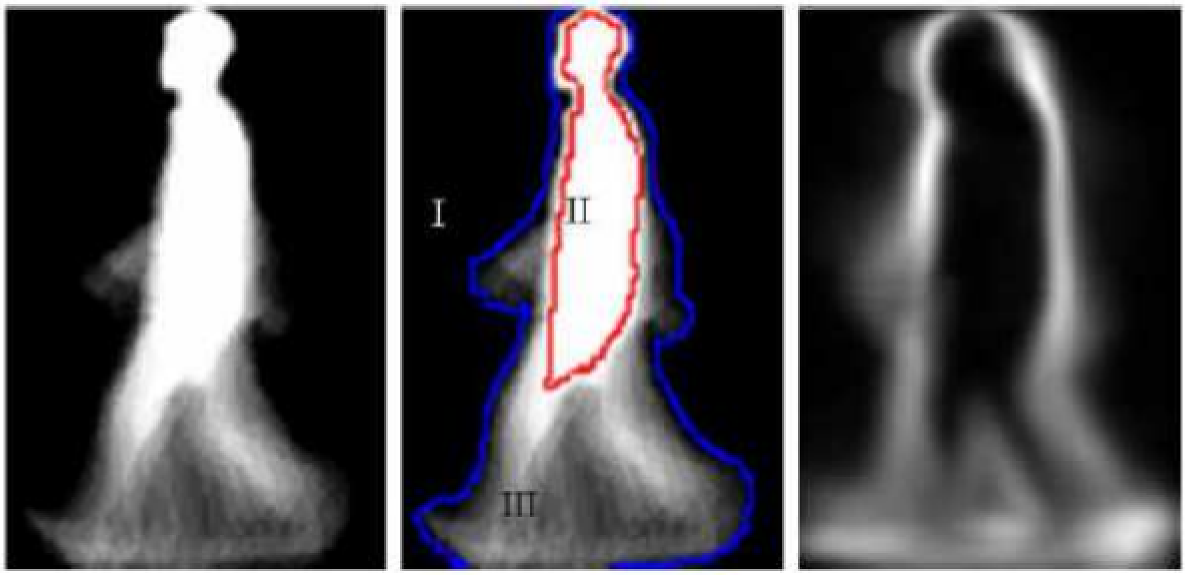

Fig. 11. First image displays an example of GEI. Second image highlights the three regions of GEI, where the dynamic region is marked as region III. Dynamics weight mask is shown in the third image (Yang *et al*., 2008)

Xu（2012年）将每个GEI表示为一组局部Gabor特征，结合了不同方位和比例的Gabor特征，使用全局高斯混合模型（GMM）进行特征学习。

Hu(2014)，把GEI描述为一组双树复数小波变换（Dual-Tree Complex Wavelet Transform DTCWT）特征。

Choudhury and Tjahjadi (2015) 计算GEI的熵，然后使用高斯滤波器进行多尺度形状分析

Zhang et al. (2010a) 提出一种Active Energy Image (AEI) 计算相邻两张图片的差，通过二维局部性保留投影（2DLPP）方法将每个AEI投影到子空间上。

Huang and Boulgouris (2012)将序列图像分为三块：头，身，腿。提出Shifted Energy Image (SEI) 根据各自的水平中心对齐每个区域

Chen et al. (2009) 提出主能量图Dominant Energy Image (DEI)，将步态周期分为不同的簇，每个簇可计算一个DEI，对群集的DEI和连续帧之间的帧差的正部分求和，然后，生成帧的帧差能量图Frame Difference Energy Image（FDEI）

Roy et al. (2012) 提出了姿态能量图Pose Energy Image (PEI)，提取每个步态周期的关键姿态

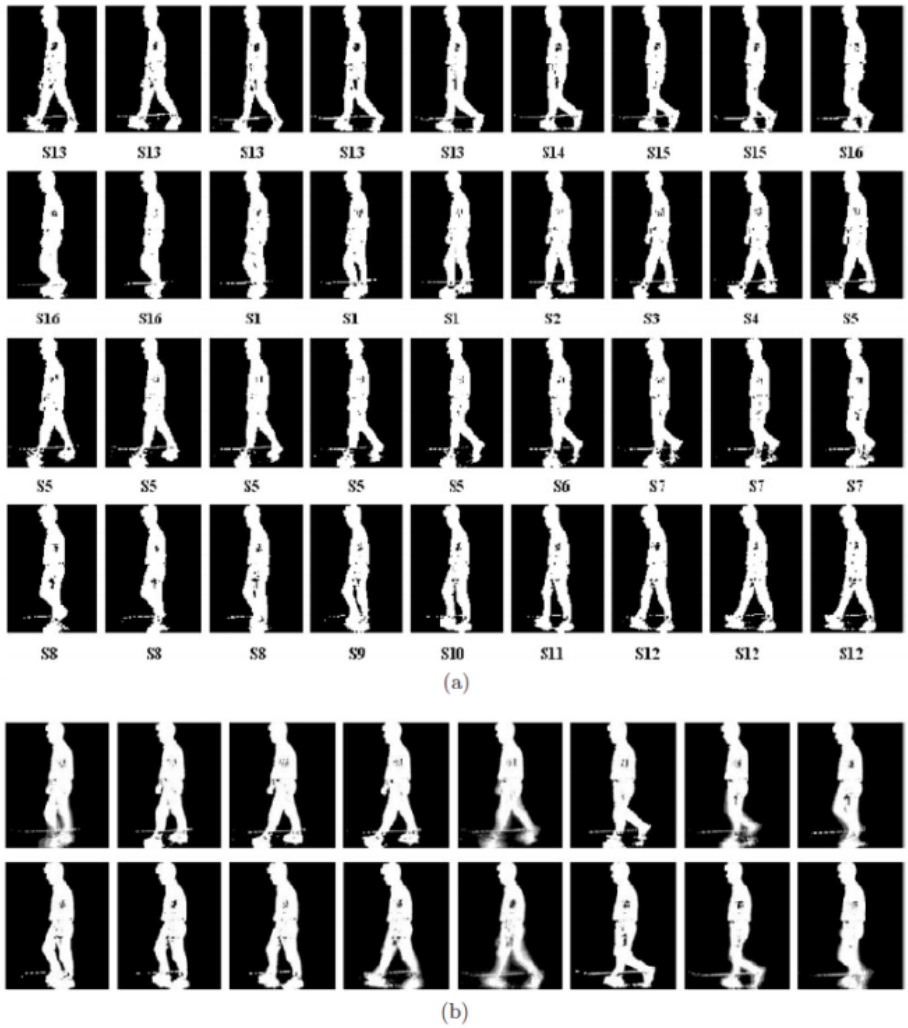

Fig. 12. (a) A sequence of silhouette in a gait cycle with the key pose labeled at the bottom of each silhouette. There is a total of 16 key poses, i.e., S1-S16. (b) The PEIs of the 16 key poses (Roy *et al*., 2012)

Table 3. Summary of model-free approaches (appearance-based representation)

Literature	Gait features	Classifier/distance metric
Bobick and Davis (2001)	MEI + MHI	Mahalanobis distance
Lee *et al*. (2014b)	TAMHI + HOG	Euclidean distance
Liu and Sarkar (2004)	Averaged silhouette	Euclidean distance
Xu *et al*. (2006)	Averaged silhouette + CSA + DATER	kNN
Han and Bhanu (2006)	GEI	Euclidean distance
Yang *et al*. (2008)	EGEI	Euclidean distance
Huang *et al*. (2013)	Modified GEI + Gabor Wavelets	SVM
Zhang *et al*. (2009)	DGEI + PCA + Locality preserving projections	Euclidean distance
Xu and Zhang (2010)	GEI + Fuzzy PCA	kNN + Euclidean distance
Moustakas *et al*. (2010)	GEI + Radial integration transform	Probability
Xu *et al*. (2012)	GEI + Gabor-PDF	Locality constrained group sparse representation
Zhang *et al*. (2010a)	AEI + 2D locality preserving projections	kNN + Euclidean distance
Huang and Boulgouris (2012)	SEI + Linear discriminant analysis	-
Chen *et al*. (2009)	FDEI + Frieze + wavelet	HMMs
Roy *et al*. (2012)	PEI	Euclidean distance

Transformation-Based Representation

主要采用主成分分析（PCA）和傅里叶变换

PCA

PCA的加强中有一种使用Procrustes形状分析将轮廓边界转换为特征空间以获得Procrustes平均形状(PMS)，再用形状上下文描述符来衡量两个PMS的相似度。

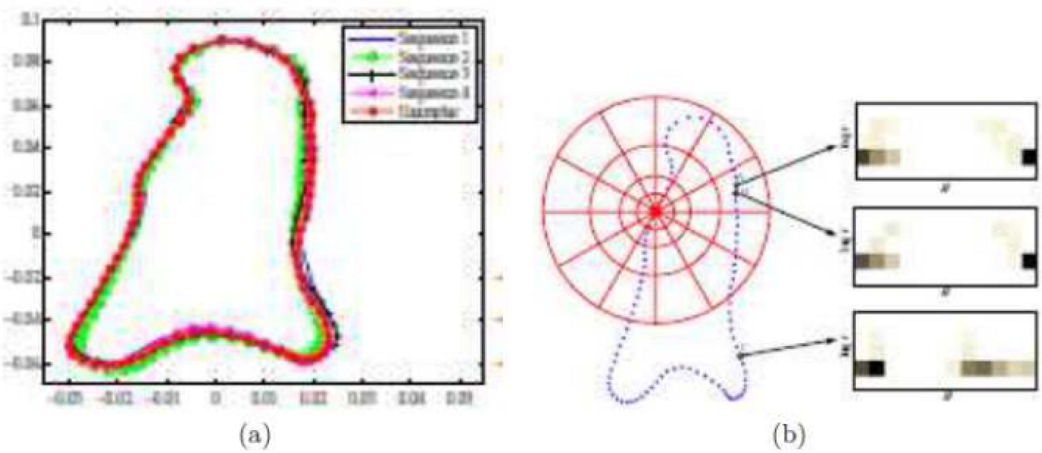

Fig. 13. (a) An example of PMS. (b) Computation of shape context for a PMS using log-polar histogram bins (Zhang *et al*., 2010b)

Zheng(2011)对GEI向量采用偏最小二乘回归以生成最佳特征向量。通过将PCA应用于最佳特征向量来获得视图转换模型（View Trasnformation Model VTM）

Kusakunniran(2011)提出成对形状配置Pairwise Shape Configuration (PSC)，随后又提出高阶形状配置Higher-order Shape Configuration (HSC)

Fourier

对变形轮廓边界进行傅立叶变换提取步态特征，主要是关键帧的特征提取

Table 4. Summary of model-free approaches (transformation-based representation)

Literature	Gait features	Classifier/distance metric
Murase and Sakai (1996)	Parametric eigenspace trajectories	Spatiotemporal correlation
Huang *et al*. (1999)	PMS + Canonical analysis	Spatiotemporal correlation
Wang *et al*. (2003a; 2003b)	PMS	Procrustes distance
Zhang *et al*. (2010b)	PMS + Shape context	kNN + Shape context distance
Zheng *et al*. (2011)	VTM	L1-norm distance
Kusakunniran *et al*. (2011a)	PSC	kNN + Procrustes distance
Kusakunniran *et al*. (2011b)	HSC	kNN + Procrustes distance
Mowbray and Nixon (2003)	Fourier descriptors	kNN + Euclidean distance
Tian *et al*. (2004)	Fourier descriptors	DTW
Lu *et al*. (2008)	Fourier descriptors (key frame profile)	kNN
Yuan *et al*. (2015)	Fourier descriptors (key frame)	Canonical Time Warping
Ohara *et al*. (2004)	3D Fourier descriptors	Cross correlation
Choudhury and Tjahjadi (2012)	PMS + elliptical Fourier descriptors	Procrustes distance + dissimilarity score
Lee *et al*. (2013)	Circular shifting + Interpolation + Fourier descriptor	Product of Fourier coefficients
Boulgouris and Chi (2007)	Radon transform + LDA	Euclidean distance

Distribution-Based Representation

基于分布的描述：常用的有光流分布，概率分布和基于纹理的分布

在光流向量中可以捕获运动强度和运动方向信息，为了实现抗噪声的鲁棒性，采用离散化流向并制定基于直方图的方向表示的方法。Gait Flow Image (GFI)

Fig. 14. The first two images show the silhouette at frame t − 1 and t respectively. The computed optical flow field is displayed in the third image (Bashir *et al*., 2009)

多分辨率局部二值模式(Local Binary Patterns LBP)可以编码时空局部二值直方图

Table 5. Summary of model-free approaches (distribution-based representation)

Literature	Gait features	Classifier/distance metric
Polana and Nelson (1994)	Optical flow	Nearest centroid
Little and Boyd (1995)	Optical flow	Euclidean distance
Bashir *et al.* (2009)	Optical flow	Euclidean distance
Lam *et al*. (2011)	GFI	kNN + Euclidean distance
Vega and Sarkar (2003)	Trace in space of probability functions	Euclidean distance/DTW
Hong *et al.* (2013)	Multivariate probability + Bernoulli mixture model	Probability
Lee *et al*. (2014a)	Binomial distribution	Kullback-Leibler divergence
Kellokumpu *et al*. (2009)	LBO-TOP	Histogram intersection
Abdolahi and Gheissari (2011)	LBP-TOP + Histograms of video-words occurrences	SVM
Hu *et al.* (2013)	Optical flow + LBP	DTW
Lee *et al*. (2015)	TBP	Euclidean distance

模式识别与分类

在给定观察到的未知类步态特征的情况下，从已知类库中识别出最佳匹配

主要使用KNN、对于时序数据使用的动态时间规整DTW(Dynamic Time Warping)、同样针对时序数据的隐马尔可夫模型(hidden Markov Model HMM)、支持向量机(Support Vector Machines SVM)

复杂的多分类模式识别问题都会被简化为二分类

神经网络也是一种常用的分类模型、特征重叠的情况下经常使用模糊逻辑，