Benefits of Gaussian Convolution in Gait Recognition

Maria De Marsico[1], Alessio Mecca[1]

Abstract: The first and still popular approach to gait recognition applies computer vision techniques to appearance-based features of walking patterns. More recently, wearable sensors have become attractive. The accelerometer is the most used one, being embedded in widespread mobile devices. Related techniques do not suffer for problems like occlusion and point of view, but for intra-subject variations caused by walking speed, ground type, shoes, etc. However, we can often recognize a person from the walking pattern, and this stimulates to search for robust features, able to sufficiently characterize this trait. This paper presents some preliminary experiments using the convolution with Gaussian kernels to extract relevant gait elements. The experiments use the large ZJU-gaitacc public dataset, and achieve improved results compared with previous works exploiting the same dataset.

Keywords: Gait Recognition, Biometrics, Gaussian Kernel

1 Introduction

New technologies can simplify everyday life, but they also introduce unprecedented security issues. Robust authentication techniques are required both in traditional settings, for instance, to prevent unauthorized access to restricted physical areas (e.g., a bank caveau), and to secure remote services (e.g., home banking), or mobile devices (e.g., smartphones). The present use of smartphones for simply making calls is definitely marginal with respect to the amount of other possible applications, often entailing the storage/use of private data. Authentication conventionally relies on something to know/remember (knowledge-based, e.g., passwords and PIN), or to be possessed (object/token-based, e.g., physical keys), or, more recently, on personal physical/behavioral features (biometrics-based, e.g., face and fingerprints) [Cl94]. Studies on the passwords managing habits [FH07, HH11], highlight memorability problems, especially for robust passwords. This causes the reuse of passwords for different services, creating security breaches. Therefore, biometrics is an attractive alternative. The biometric traits that can be exploited for authentication/identification purposes, include the popular fingerprints, face and iris. These traits have some ”strong” properties, such as uniqueness, universality, and permanence, joined with a high recognition capability. This allows using them as a valid substitute for passwords or keys, especially in controlled conditions. Other traits, e.g., hand geometry, signing dynamics, hair color, height, may lack one of the properties mentioned above, and produce less accurate recognition performances or rather distinguish groups of individuals. For these reasons, they are considered as ”soft”. Gait falls in this category, due to variations caused by both extrinsic (ground slope, shoes) and intrinsic (speed, temporary physical problems) factors. However, several studies investigate its discriminative power with interesting results.
The human gait follows strict bio-physiological rules [Va99]. In general, walking requires

[1] I3S, Computer Science, Via Salaria, 113, {demarsico, mecca}@di.uniroma1.it

both the periodic movement of each foot from one position of support to the next, and sufficient ground reaction forces [RIT81]. The periodic leg movement is the essence of the naturally stereotyped cyclic nature of human gait, but energy saving kinematic strategies change across individuals. These strategies produce features that make individual walking patterns recognizable [BBL96]. Gait recognition can be carried out by computer vision techniques (from videos), by the analysis of signals captured with equipped floors or, more recently, with data coming from the accelerometers and other sensors embedded into wearable devices. This latter type of gait analysis has been taken into account in this paper. The main contribution of this work is a study on the effects of the convolution of gait signals, either segmented or not, with Gaussian kernels defined by various values of σ.

2 Related Work

Recognition methods based on gait signals from wearable devices fall into two main categories. The methods in the first category preliminarily divide the signal into steps [DMM16] or cycles (right and left step or vice versa) [DBH10, Ro07, GSB10, Fe16, Ju12, PZW09, GR16, Gi17]. These works generally exploit simple signal matching algorithms like Manhattan or Euclidean distances or, in order to reduce misalignment problems, use them as distances metrics for DTW-like algorithms. The methods in the second category divide the signal into fragments (or chunks) [KWM10, Ni11, NWB12, Lu14]. The difference between steps/cycles and fragments is that the former are related to gait dynamics, and are identified by specific signal characteristics related to gait phases, while the latter are simple signal slices with the same number of samples, with no correspondence with physiology. These works generally use machine learning techniques to train a classifier per subject. Most of them apply recognition in verification mode, with an implicit identity claim (the ownership of the device). A few proposals do not rely on a preliminary step segmentation procedure, in particular [Zh15], which is presented with more details below, and one out of the five recognition strategies in [DMM16]. The use of unsegmented signals for the matching phase, even if it seems to provide good results, might provide degraded performance if the walking signals to match have a very different length. This can be avoided in either explicitly or implicitly controlled acquisition. An example of data acquisition triggered by Bluetooth devices (beacons) is presented in [DMM17].
The experiments in this paper exploit the ZJU-gaitacc dataset presented as a public benchmark in [Zh15]. The recognition approach proposed in the same work is therefore used for comparison, so that it is described in more details. It exploits and refines the concept of Signature Points (SPs) already presented in [PZW09]. Each walk is first converted into its 1D magnitude vector (*mv*) form, given by the usual formula ($\forall i,\quad mv[i] = \sqrt{x_i^2 + y_i^2 + z_i^2}$), where x_i, y_i, and z_i are respectively the samples on the three axes at time i. As already mentioned, this work exploits the entire unsegmented walking signal. SPs are defined as informative points in the *mv*, and are chosen as the extrema of the convolution of the *mv* with a Difference of Gaussian (DoG) pyramid. Referring to the work in [Lo04], the authors claim that these extrema "are shown to be stable, scale-invariant, and at informative localities". SPs are marked with multi-scale local descriptors. The descriptors are stored as vectors, and all vectors for all gallery users are collected in a dictionary matrix. Vectors

are then clustered considering that descriptors extracted from similar gait phases are generally similar (”*phase propinquity*”). The matrix of centroids is used to extract the closest subdictionary for a certain probe, in order to code it as a linear combination of its columns. Matching is treated as a conditional probability problem and uses a sparse-code classifier. A reason for choosing this work for comparison is the use of Gaussian convolution (in that case a DoG pyramid), similarly to our proposal. Moreover, the dataset exploited, namely the ZJU-gaitacc, differently from other works, allows comparing results.

3 Proposed Strategy

The presented strategy is an evolution of the proposal in [DMM16]. It is not feasible to carry out a preprocessing step to discard the first and the last points in the signals, which are usually either noise or unstable information. This step is usually guided by the knowledge of the conditions that trigger the acquisition. For example, this is manually triggered by a user tap on the phone screen in the case of the dataset (BWR) in [DMM16], resulting in some useless points between the tap/start action and the real start of the walking action (and the same for the stop/end action). Information about such conditions is not available for the ZJU-gaitacc dataset. The step segmentation algorithm has been slightly modified w.r.t. [DMM16]. It relies on the `stepThreshold` and `stepEquilibrium` parameters. They are computed over the y axis, which is the dominant one in the considered setting. Segmentation results on y are then mapped onto the other two axes. The `stepThreshold` is determined as the k-th highest relative maximum of the signal, where k is the estimated number of steps. It identifies signal peaks high enough to be considered as start/end of a step. The `stepEquilibrium` is used to avoid considering sufficiently high peaks yet not sufficiently separated from eligible ones. In [DMM16] it is computed as the value lower than the signal average, having the highest frequency. In the present work, the value for `stepEquilibrium` is rather computed as $\mu - \sigma$ where μ is the mean and σ is the standard deviation of the walking signal in analysis. This formulation provides better results.
For reader convenience, the complete step segmentation algorithm is reported here.

1) compute `stepEquilibrium`
2) compute `stepThreshold`
3) find the first relative maximum - set it as starting point of the first step
4) find the next value lower than `stepEquilibrium`;
5) if end of the signal is reached: END
6) find the next relative maximum greater than `stepThreshold` - set it as current step ending point and next step starting point
7) if not end of signal, repeat from 4

The approach further entails an outliers removal phase. It computes the average Dynamic Time Warping (DTW) distance of each step from all the others, and then discards all steps for which it is greater than the average of average distances plus their standard deviation. As a further difference, the method in [DMM16] avoids re-computing segmentation parameters from the probe, by using a fitting procedure, to avoid re-segmenting the probe signal knowing its number of steps. The incoming signal is rather segmented from time to time using the stored parameters of the gallery walk to match. In the present work the overall segmentation procedure is repeated for the incoming probe. The slightly modified computation of `stepEquilibrium` threshold and probe segmentation aim at a better adaptation to the use of different acquisition devices. In fact, we notice that the stored

`stepThreshold` and `stepEquilibrium` depend on the values measured on the y axis during the enrollment. If the walking signal from the probe is acquired from the same user but with a different device, these parameters can vary significantly. The new algorithm provides a better segmentation accuracy on the BWR-MultiDevice dataset presented in [DMDPM16]. Even if data in ZJU-gaitacc is acquired by devices of the same kind, it is well known that also accelerometers of the same brand and model, can provide different values in identical conditions. Actually, it is not reported in the dataset presentation whether the same device was always used in the same position. Therefore this work exploits the modified version of the segmentation algorithm. The knowledge of k seems limiting, but it can be estimated by applying a step counter algorithm. Moreover, the precise knowledge of k is not even so important, given that it is reasonable for the signals at hand. This is due to the way k is used, and to the fact that after a certain number of steps, if no exceptional event happens, the gait pattern tends to stabilize [Fe17]. For instance, in the presented experiments k has been set to 10 for all walks (as for [DMM16]). However, the single walks in ZJU-gaitacc probably contain more than 10 steps (they are about 20 meters long), but the same value of k has been successfully used.
As for the matching strategy, two of the algorithms proposed in [DMM16] are exploited, namely *WALK* and *ALL STEPS VS. ALL (AVSA)*, to get comparable results. They both rely on the classical implementation of DTW; WALK compares entire signals, while AVSA exploits single steps. In particular, given two walks to compare, the best correspondence is searched for each step of the first walk, by comparing it with each step of the second one, and taking the best result. The final score is the average of these best matchings. The process should be repeated by inverting the role of the two walks and the average should be taken to obtain a symmetric distance. However experiments demonstrated that the incremented computational demand does not correspond to more accurate results.
The present contribution w.r.t. [DMM16] is twofold. The first one is the improved segmentation algorithm. The second and most relevant one is the investigation of the effects of the convolution of signals, either segmented or not, with Gaussian kernels, before comparison. In the experiments, 4 different values for the σ of the Gaussian kernel are tested, namely 2, 4, 8, and 16, and also the possibility of a score-level fusion between 2 or more results. This fusion is obtained from the distance values computed matching the different convolved gait data, by either picking up the best one or by summing them up. In summary: 1) the signals are possibly divided into steps; 2) different Gaussian kernels are used for convolution with the original signal; 3) distances are computed according to either WALK or AVSA; 4) the results are fused by taking either the best or the sum of them.

4 Results and Discussion

The results are presented in terms of Equal Error Rate (EER) for verification (VER), Recognition Rate (RR) for closed set identification (CSI), and both EER and Detection and Identification Rate at rank 1 for a given threshold t (DIR(1,t)), for open set identification (OSI). In OSI some probes may not belong to enrolled users, so that a reject option is added and an acceptance threshold t is required. Therefore, the performance measures are a kind of combination of those used for VER and CSI. The DIR(1,t) is similar to the RR.

It measures the percentage of genuine probes that conform two conditions: the right identity of the probe is in the first position of the distance ordered list, and its distance meets the acceptance threshold. FRR(t) is computed as 1-DIR(1,t), and FAR(t) is the percentage of impostor probes that meet the acceptance threshold, whichever the returned identity. Therefore, it is possible to compute the EER. In the reported results, in order to present a consistent view of system performance, DIR(1,t) refers to the same threshold of the ERR.
This work exploits the dataset ZJU-gaitacc [Zh15] that is one of the largest freely available. It collects gait signals from 153 subjects, with 12 walks each captured during 2 sessions. Further 22 subjects have only 6 walks from a single sessions. Walks are long enough to allow extracting sufficient stable features. Data is acquired by 5 accelerometers of the same kind (WiiMote) in different body placements: left upper arm, right wrist, right hip, left tight and right ankle. The achieved performance reach an up to 95.8% of RR (CSI), and a down to 2.2% of EER (VER), when combining results from all the accelerometers. OSI is not tested. We only exploit the right hip subset, since it is the most popular location for experiments using accelerometers embedded in smartphones, and the one over which the work presenting the dataset achieves the best average results (RR=73.4% for CSI and EER=8.9% for VER). As a negative aspect, data from ZJU-gaitacc are interpolated and it is not possible to get the original/raw signals. The dataset OU-ISIR [Ng14] is even larger, with 744 subjects. However, differently from ZJU-gaitacc, the walks are much shorter, manually segmented according to ground shape, and captured in a single session.
Besides the modalities in the experiments in [Zh15], the results presented here also pertain to the already mentioned OSI, and to verification with more gallery templates per subject (VER_MULTI). In the latter case, when verifying a probe claimed identity, all corresponding gallery templates are matched and the best result is returned. This decreases the effect of intra-class variations. As a matter of fact, multi-template strategy is often exploited in literature to this aim and to improve performance by decreasing the FRR.
Table 1 summarizes the results achieved with different Gaussian kernels or their combinations. Combinations differ for both the number of kernels involved, and for the computation of the final result. The latter is obtained either by choosing the best score among those returned by the kernels in the combination (Combined BEST - C_BEST), or by summing up all these scores (Combined SUM - C_SUM). WALK, that compares the entire gait signal, confirms itself as better than ALL STEPS VS. ALL (AVSA), that rather exploits step segmentation. C_SUM always achieves better identification results than single kernels in CSI, independently from the chosen combination and from the recognition strategy (with or without segmentation). Identification results in CSI obtained by C_BEST are generally worse than those obtained by single kernels. In VER mode, WALK achieves an EER from 0.334 to 0.348, depending on the kernel/combination, with the best value obtained in different settings, that include both a single kernel or a different combinations. AVSA achieves an EER from 0.354 to 0.3674, with a single best value obtained by Gaussian kernel with $\sigma = 2$. In this modality, C_SUM generally achieves worse results, while C_BEST overcomes single kernels. As expected, a significant improvement of performance is achieved by VER_MULTI w.r.t. VER (in practice, an order of magnitude). WALK achieves an EER between 0.036 and 0.046, while AVSA has an EER from 0.0395 to 0.061, which reveals a higher dependence on the chosen kernel/combination. As for WALK, C_BEST and C_SUM achieve comparable results also with single kernels. On the

Tab. 1: Results with different single Gaussian kernels or combinations. The bold values are the best result(s) for each sub-category (recognition modality - kernel(s)), the green background identifies the best result(s) for the modality. The last two rows report performance of the compared works.

	WALK					ALL STEPS VS. ALL				
Gaussian Kernel	Identification Closed Set	Verification Single	Verification Multi	Identification Open Set ERR	DIR(1, t)	Identification Closed Set	Verification Single	Verification Multi	Identification Open Set ERR	DIR(1, t)
Single Gaussian										
2	0.9286	0.343	**0.039**	0.249	0.7512	**0.8581**	**0.3540**	0.0610	0.3240	0.6840
4	**0.9641**	0.337	0.046	0.226	0.7745	0.8559	0.3577	0.0550	0.2953	0.6818
8	0.9613	**0.334**	**0.039**	**0.209**	0.7908	0.8575	0.3674	0.0485	**0.2877**	0.7407
16	0.9341	0.355	**0.039**	0.248	0.7522	0.8302	0.3669	**0.0397**	0.2918	0.6665
Combined BEST - C_BEST										
2-4	**0.9641**	**0.334**	0.046	0.226	0.7740	0.8553	**0.3567**	0.0532	0.3103	0.7129
2-8	0.9613	0.339	**0.039**	0.209	0.7908	**0.8575**	0.3587	0.0469	**0.2737**	0.7249
2-16	0.9341	0.342	**0.039**	0.248	0.7522	0.8302	0.3581	**0.0395**	0.2950	0.6954
4-8	0.9613	0.341	**0.039**	0.209	0.7908	0.8570	0.3603	0.0476	0.2811	0.7325
4-16	0.9341	**0.334**	**0.039**	0.248	0.7522	0.8308	0.3602	0.0397	0.2975	0.7069
8-16	0.9346	0.35	0.04	0.248	0.7522	0.8297	0.3630	0.0407	0.3032	0.7134
2-4-8	0.9619	0.338	**0.039**	**0.208**	0.7908	0.8570	0.3592	0.0472	0.2740	0.7249
2-4-16	0.9341	0.342	0.04	0.248	0.7522	0.8308	0.3592	0.0397	0.2950	0.6954
2-8-16	0.9346	0.343	0.04	0.248	0.7522	0.8297	0.3596	0.0401	0.2956	0.6954
4-8-16	0.9346	0.344	0.04	0.248	0.7522	0.8297	0.3612	0.0401	0.2983	0.7063
ALL	0.9346	0.343	0.04	0.248	0.7522	0.8297	0.3600	0.0401	0.2956	0.6954
Combined SUM - C_SUM										
2-4	0.9662	**0.334**	0.046	0.232	0.7669	0.8652	0.3593	0.0581	0.3092	0.7074
2-8	0.9711	0.338	0.043	0.208	0.7919	0.8843	**0.3589**	0.0496	0.2729	0.7456
2-16	**0.9728**	0.343	0.042	0.199	0.8007	**0.9001**	0.3640	0.0426	0.2535	0.7544
4-8	0.9641	0.34	0.042	0.208	0.7919	0.8723	0.3629	0.0509	0.2606	0.7183
4-16	0.9657	0.345	0.038	0.197	0.8028	0.8919	0.3622	0.0427	**0.2364**	0.7325
8-16	0.9602	0.348	**0.036**	0.2	0.8001	0.8739	0.3669	**0.0411**	0.2680	0.7484
2-4-8	0.9679	0.338	0.044	0.21	0.7898	0.8783	**0.3589**	0.0491	0.2860	0.7369
2-4-16	0.9722	0.341	0.042	0.203	0.7963	0.8930	0.3635	0.0445	0.2680	0.7636
2-8-16	0.9711	0.344	0.039	0.199	0.8045	0.8925	0.3617	0.0436	0.2489	0.7571
4-8-16	0.9673	0.345	0.039	**0.195**	0.8001	0.8843	0.3637	0.0439	0.2448	0.7369
ALL	**0.9728**	0.342	0.041	0.2	0.7996	0.8936	0.3605	0.0474	0.2615	0.7642
[DMM16]	0.9282	0.3269	0.0926	0.3233	-	0.714	0.3476	0.3625	0.5397	-
[Zh15]	Identification: RR=0.734					Verification: EER=0.089				

contrary, AVSA achieves generally worse results with single kernels, while C_BEST seems to be a little bit better than C_SUM. Finally, in OSI, which is the hardest modality, C_SUM obtains the best result both with WALK and AVSA. In summary, it is possible to observe that C_SUM is the best option for both CSI and OSI. C_BEST seems to be to prefer for both VER and VER_MULTI. In general, combinations work better than single kernels. Table 1 also reports the results of compared works. The values achieved in [DMM16] for WALK are RR=0.9282 for CSI, EER=0.3269 for VER, EER=0.0926 for VER_MULTI, and EER=0.3233 for OSI. There is therefore an improvement, except for VER. As for AVSA, RR=0.714 for CSI, EER=0.3476 for VER, EER=0.3625 for VER_MULTI, and EER=0.5397 for OSI. In this case, the improvement is even greater and generalized. The results in [Zh15] for the right hip are RR=0.734 (CSI) and EER=0.089 (VER). While identification results are significantly increased, improved verification is obtained only when considering a gallery with more templates per user.

5 Conclusion

The paper presented the results of a preliminary investigation of the use of Gaussian kernels to process gait signals. The aim is to attempt a new strategy to extrapolate those periodic characteristics that allow recognizing a person from the walking pattern. Experiments are carried out on a large public dataset, to allow a wide comparison of results. Though achieving improved outcomes, the experiments testify that further investigations of the features evidentiated by different Gaussian kernels can allow achieving a better generalized accuracy. It is worth pointing out that, of course, testing is carried out over static data for which ground truth is available. Several dynamic authentication scenarios are possible. For example, using a suitable smartphone app to capture the walking signal of an approaching enrolled user, it is possible to identify the walker and automatically grant access to a restricted area. The smartphone ID alone, once stored in the system, would not be sufficient to provide authentication, given the possibility that it is kept by a different subject. However, the same ID could be used as an implicit identity claim, to exploit the lighter verification modality.

References

[BBL96] Borghese, N Alberto; Bianchi, L; Lacquaniti, F: Kinematic determinants of human locomotion. The Journal of physiology, 494(3):863–879, 1996.

[Cl94] Clarke, Roger: Human identification in information systems: Management challenges and public policy issues. Information Technology & People, 7(4):6–37, 1994.

[DBH10] Derawi, Mohammad O; Bours, Patrick; Holien, Kjetil: Improved cycle detection for accelerometer based gait authentication. In: Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on. IEEE, pp. 312–317, 2010.

[DMDPM16] De Marsico, Maria; De Pasquale, Daniele; Mecca, Alessio: Embedded Accelerometer Signal Normalization for Cross-Device Gait Recognition. In: 15th Int. Conf. of the Biometrics Special Interest Group (BIOSIG). IEEE, pp. 1–5, 2016.

[DMM16] De Marsico, Maria; Mecca, Alessio: Biometric Walk Recognizer - Gait recognition by a single smartphone accelerometer. Multimedia Tools and Applications, 2016.

[DMM17] De Marsico, Maria; Mecca, Alessio: Gait Recognition: The Wearable Solution. Human Recognition in Unconstrained Environments: Using Computer Vision, Pattern Recognition and Machine Learning Methods for Biometrics, pp. 177–195, 2017.

[Fe16] Fernandez-Lopez, Pablo; Liu-Jimenez, Judith; Sanchez-Redondo, Carlos; Sanchez-Reillo, Raul: Gait recognition using smartphone. In: Security Technology (ICCST), 2016 IEEE International Carnahan Conference on. IEEE, pp. 1–7, 2016.

[Fe17] Fernandez-Lopez, Pablo; Sanchez-Casanova, Jorge; Tirado-Martín, Paloma; Liu-Jimenez, Judith: Optimizing resources on smartphone gait recognition. In: Biometrics (IJCB), 2017 IEEE Int. Joint Conference on. IEEE, pp. 31–36, 2017.

[FH07] Florencio, Dinei; Herley, Cormac: A large-scale study of web password habits. In: Proceedings of the 16th international conference on World Wide Web. ACM, pp. 657–666, 2007.

[Gi17] Giorgi, Giacomo; Martinelli, Fabio; Saracino, Andrea; Sheikhalishahi, Mina: Try Walking in My Shoes, if You Can: Accurate Gait Recognition Through Deep Learning. In: International Conference on Computer Safety, Reliability, and Security. Springer, pp. 384–395, 2017.

[GR16] Gadaleta, Matteo; Rossi, Michele: Idnet: Smartphone-based gait recognition with convolutional neural networks. arXiv preprint arXiv:1606.03238, 2016.

[GSB10] Gafurov, Davrondzhon; Snekkenes, Einar; Bours, Patrick: Improved gait recognition performance using cycle matching. In: Advanced Information Networking and Applications Workshops (WAINA), 2010 IEEE 24th International Conference on. IEEE, pp. 836–841, 2010.

[HH11] Hayashi, Eiji; Hong, Jason: A diary study of password usage in daily life. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, pp. 2627–2630, 2011.

[Ju12] Juefei-Xu, Felix; Bhagavatula, Chandrasekhar; Jaech, Aaron; Prasad, Unni; Savvides, Marios: Gait-id on the move: Pace independent human identification using cell phone accelerometer dynamics. In: Biometrics: Theory, Applications and Systems (BTAS), 2012 IEEE Fifth International Conference on. IEEE, pp. 8–15, 2012.

[KWM10] Kwapisz, Jennifer R; Weiss, Gary M; Moore, Samuel A: Cell phone-based biometric identification. In: Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on. IEEE, pp. 1–7, 2010.

[Lo04] Lowe, David G: Distinctive image features from scale-invariant keypoints. International journal of computer vision, 60(2):91–110, 2004.

[Lu14] Lu, Hong; Huang, Jonathan; Saha, Tanwistha; Nachman, Lama: Unobtrusive gait verification for mobile phones. In: Proceedings of the 2014 ACM international symposium on wearable computers. ACM, pp. 91–98, 2014.

[Ng14] Ngo, Thanh Trung; Makihara, Yasushi; Nagahara, Hajime; Mukaigawa, Yasuhiro; Yagi, Yasushi: The largest inertial sensor-based gait database and performance evaluation of gait-based personal authentication. Pattern Recognition, 47(1):228–237, 2014.

[Ni11] Nickel, Claudia; Busch, Christoph; Rangarajan, Sathyanarayanan; Möbius, Manuel: Using hidden markov models for accelerometer-based biometric gait recognition. In: Signal Processing and its Applications (CSPA), 2011 IEEE 7th International Colloquium on. IEEE, pp. 58–63, 2011.

[NWB12] Nickel, Claudia; Wirtl, Tobias; Busch, Christoph: Authentication of smartphone users based on the way they walk using k-NN algorithm. In: Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2012 Eighth International Conference on. IEEE, pp. 16–20, 2012.

[PZW09] Pan, Gang; Zhang, Ye; Wu, Zhisheng: Accelerometer-based gait recognition via voting by signature points. Electronics letters, 45(22):1116–1118, 2009.

[RIT81] Ralston, HJ; Inman, V; Todd, F: Human walking. Baltimore: Williams and Wilkins, 1981.

[Ro07] Rong, Liu; Jianzhong, Zhou; Ming, Liu; Xiangfeng, Hou: A wearable acceleration sensor system for gait recognition. In: 2007 2nd IEEE Conference on Industrial Electronics and Applications. IEEE, pp. 2654–2659, 2007.

[Va99] Vaughan, Christopher L; Davis, Brian L; Jeremy, CO et al.: Dynamics of human gait. 1999.

[Zh15] Zhang, Yuting; Pan, Gang; Jia, Kui; Lu, Minlong; Wang, Yueming; Wu, Zhaohui: Accelerometer-based gait recognition by sparse representation of signature points with clusters. IEEE transactions on cybernetics, 45(9):1864–1875, 2015.