Human Gait Recognition Based on Ground Reaction Forces in Case of Sport Shoes and High Heels

Derlatka Marcin
Dept. of Biocybernetics and Biomedical Engineering
Bialystok University of Technology
Wiejska 45c, 15-351 Bialystok
m.derlatka@pb.edu.pl

***Abstract*— Currently, one of the most interesting and quickly growing issues is biometrics. Among many techniques of behavioural biometrics, the human gait recognition deserves special attention. The aim of this work is to check how the quality of a biometrics system based on ground reaction forces will change in the case of women walking in two types of footwear: sports shoes and high heels. The research was carried out based on measurements from 81 people (more than 2 700 gait cycles). The correct classification rate depended on the selected scenario of research and was in the range from 69% to 99%. The work presents the limitations and possibilities of use of human gait recognition. It also shows, that the results depend on the experience of the person walking in high heels.**

Keywords— human gait recognition, ground reaction forces, high heels, decision fusion.

I. INTRODUCTION

Human gait recognition is one of behavioural biometrics. The usage of gait as biometrics is based on the assumption that the movement pattern formed during the development of an individual is unique to a specific person. The human movement is a result of the cooperation of the skeletal, muscular and nervous systems, and after the developmental period it remains practically unchanged. It gives us possibility to use gait recognition e.g in forensic field [22].

In [12] there is a division of works regarding the issue of human gait recognition depending on the measured signal describing this occurrence. The listed methods are:

- methods using images from video cameras or the Kinect controller [1,18,23],
- sensors making measurements at the moment of contact of the foot with a surface such as pressure sensors (e.g. force plates [11]) or switch sensors (e.g. photo interrupter sensors [24]),
- mobile sensors such as accelerometers [12].

The chosen method of measurement determines the possibilities of application, but also the limitations. The most popular methods of human gait recognition are methods utilising video footage. In these methods the registered human movement is processed, usually frame by frame, into silhouette sequences. Next, through simple averaging of silhouettes across a gait cycle, the Gait Energy Image (GEI) is obtained, which ensures a high level of correct recognitions even when using low resolution camera [16]. The unquestionable benefits of this group of methods are: the possibility to register free movement of many individuals at the same time which is caused by the general acceptance of the presence of cameras in or on buildings. Of course an obvious benefit is also the possibility to register the gait of an individual even from a significant range. The problems in recognition using methods based on video cameras are caused, among other things, by changes of clothing of the analysed individual, the possibility of the analysed individual to be blocked from view by another person, changes in lighting and the sensitivity of some of the parameters describing human gait to the camera angle in relation to the analysed person [14].

Such problems are not an issue in the second group of methods. In this case it is required for the analysed subject to pass through a previously prepared measuring path, equipped with hidden measuring devices. The pressure of the foot on the measuring device enables the measurement of: ground reaction forces (GRF) [19], the distribution of the pressure of forces under the foot, footprint or foot contact time with the ground [6]. The smaller popularity of this group of methods results from the fact that, measurement is possible only when the analysed individual is made to walk through the measuring path (e.g. security gates at the airports, in stores etc.).
The last group of methods listed above assumes the full cooperation of the analysed individual while conducting the measurements. Such person is equipped with devices such as: accelerators [8], opto-reflective markers placed directly on the person's skin or tigh fitting wear [15] . Accelerators may be attached to the lower limbs of the analysed person or they can be a part of another device (e.g. mobile phone) [17].

Regardless of the chosen measurement method, the pre-processing of data or the classifiers used, one of the basic problems of human gait recognition is the influence of the shoe on the change of the movement pattern of a person [4]. In many papers related to biomechanics changes in a range of parameters describing human gait were discussed in the most noticeable of examples – the gait of women in high-heeled shoes. The article [7] states that the increase in heel height of a women's shoe results in lower walk speed, shorter strides, with an almost identical cadence. Blanchette et al. in [3] relates the increase in heel height to an increase of the value of all GRF components. Additionally, the authors states that such shoes cause an increase of angle value in the main joints of the lower limb in the sagittal plane. Moreover in [2] it has been shown that the heel lifts exerted greater muscle activity before and after heel strike. A significant increase in the activity of a range of muscles of the lower limbs was also noted in [21]. Authors in [9], noticed that the influence of high-heeled shoes on the lumbar lordosis and pelvis position depends on the frequency of wearing such shoes. In the case of experienced users hyperlordosis and pelvic anteversion was noted and in the case of unexperienced users the rectification of the lumbar spine and pelvic retroversion was noted. It is worth mentioning that in [21] there was no notable difference in the EMG activity and joint movements between experienced and unexperienced high heels users.

In the case of studies relating to the human gait biometrics, the issue of subjecs walking in high heels is discussed relatively rarely. One of such few attempts is the work by [15], which uses data from the motion capture system (Vicon) from 10 volunteers (160 gait strides) walking in four shoes with different heel heights. The analysis of the obtained results of human recognition showed that in the case of a large difference in heel height, correct classification was obtained only in 72.5% of cases.

Connor conducted barefoot gait recognition and shod-foot recognition when the shoe used in training was: the same or different from the test shoe. The obtained correct recognition rate (CCR) in this last case was 90.5%. It needs to be stressed, however, that the used dataset had data from 92 subjects, mostly men [6].

In turn, in [7] based on data from video cameras analysis was conducted, among other things, on the influence of the type of the worn shoes on the degree of human gait recognition. The analysed shoes included: normal shoes, formal shoes (dress shoes for male and high-heeled shoes for female) and casual wear (slippers). CCR for the individual shoe types was respectively: 81.25%, 78.84% and 80.65%. 125 subjects took part in the study.

The aim of this work is the analysis of the influence of wearing high heeled shoes on the human gait recognition based on ground reaction forces.

II. Materials and Methods

A. Materials

The measurements were made in the Bialystok University of Technology on a group of 81 women. The people taking part in the research were at ages 21.38 ± 1.23, body weight: 62.5 ± 11.37 kg and body height 166.06 ± 5.66 cm.

Each of the analysed subjects was informed before the experiment of its aim and the measurement method and signed a consent to participate in the study. Prior to gait measurement there was a short survey conducted, with questions about the preferred types of footwear. As many as 60 subjects (21.49 ± 1.24 years, 63.39±11.48 kg, 166.59±5.65 cm) answered that they prefer sports shoes in their day to day life, 20 women (21.1±1.24 years, 60.8±11.49 kg, 165.14±5.5 cm) preferred high heeled shoes, and one person said that the time they spend in sports shoes and high heeled shoes is more or less the same.

During the measurement the analysed individual walked over a measuring path, with two hidden force plates made by Kistler (60cm x 40cm, 960Hz). The people were not informed about the presence of the plates or any requirement to hit their foot directly on them. In the case when the person put their foot outside the plate or on its edge, the measurement was repeated with a slight modification to the starting place of the walk.

Each of the analysed subjects walked in their own footwear: sports shoes and high heeled shoes, with the condition that the high heeled shoe should have the highest possible heel for that person. Each person had 14-20 gait strides registered for each footwear type, which gave a total of 2 761 gait strides. Investigation for both types of footwear were conducted on the same day to eliminate psychophysical factors such as health condition, mood etc. from the study. During the experiment, after every 10 gait strides of a single person there was a short 1-2 minute break, in order to avoid tiredness.

This work uses the best method of classification of the ones presented in the work by [10] which is why it will be only briefly described here.

B. Cycle of human gait

Human gait in its normal form is a cyclical phenomenon. It is assumed that the cycle gait begins on the moment of the initial contact (IC) of the reference lower limb.

There are two phases distinguished in the gait cycle:

- the support phase – when the reference lower limb is in contact with the ground;
- the swing phase – when the reference leg is moved forward, there is no contact with the ground.

Five sub phases can be distinguished in the support phase, which lasts approximately 60% of the entire gait cycle:

- Initial Contact (IC) –in this phase the foot begins contact with the ground. In typical gait the initial contact is made by human heel and it is called heel strike (HS).
- Loading response (LR) – it takes place from the end of the IC until the toes of the second foot lose contact with the ground. It lasts 0% - 10% of the entire gait cycle.
- Mid-stance (MidSt) – it is the phase between toes of the opposite foot losing contact with the ground and moment when body weight is aligned over the forefoot. The analyzed foot rests flat on the surface. It is the period of about 10% to 30% of the entire time of the gait cycle.
- Terminal Stance (TSt) – it is the phase from rising the heel of the reference leg and finishing with initial contact of the opposite leg. This period happens from about 30% to 50% of the gait cycle

- Pre-swing (PreSw) – begins with IC of the opposite leg and finishes with the toe off of the analyzed lower limb. Interval: 50-60% of gait cycle.

C. *Measured signals*

During the support phase of human walk, the forces generated between the foot and the surface are called the ground reaction forces. There are three components to these forces: anterior-posterior *Fx*, vertical *Fy* and lateral *Fz* (Fig. 1).

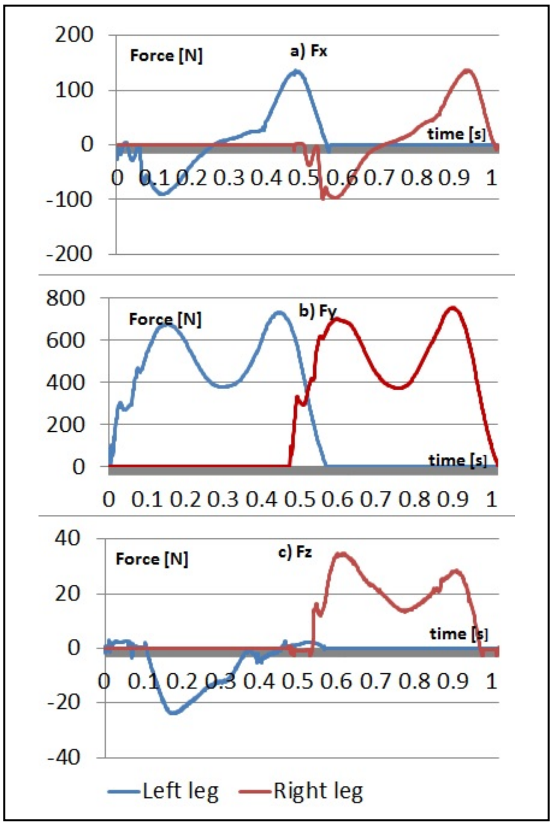

Fig. 1. The three components of GRF in: a) anterior/posterior, b) vertical and c)medial/lateral direction. The gait in high-heeled shoes (the subject's body height 165.7 cm; body weight 61.3 kg, age 21 years).

In the vertical GFR component there can be noticed two maximums and one minimum. The maximums of the vertical GRF reach approximately 120% and the minimum approximately 80% of the body weight of the analysed person. In the case of the anterior-posterior GRF component the negative initial value is a result of the braking of the reference lower limb – the direction of the force vector is opposite to the direction of the walk. Similarly, a positive value is a result of acceleration ending with pushing the toes off the surface. The value of the lateral component *Fz* depends on the analysed lower limb. It is generally assumed that the *Fz* values are positive for the left lower limb, and negative for the right lower limb. The value of those forces are approximately 10% of the body weight of the analysed person. A more precise description of the individual components can be found in e.g. [10].

D. *Preprocessing*

The ground reaction forces registered using the force plates are presented as a time series: $x_1, x_2, \ldots, x_n$, where n – is the number of samples, which depends on the length of the support phase. To compare between the time series, a well-known dynamic time warping algorithm (DTW) was used. DTW searches for the optimum so called warping path, which allows to map one time series onto another. The cost of such mapping is higher, the less similar are the compared series, which is why DTW can be treated as a measurement of distance.

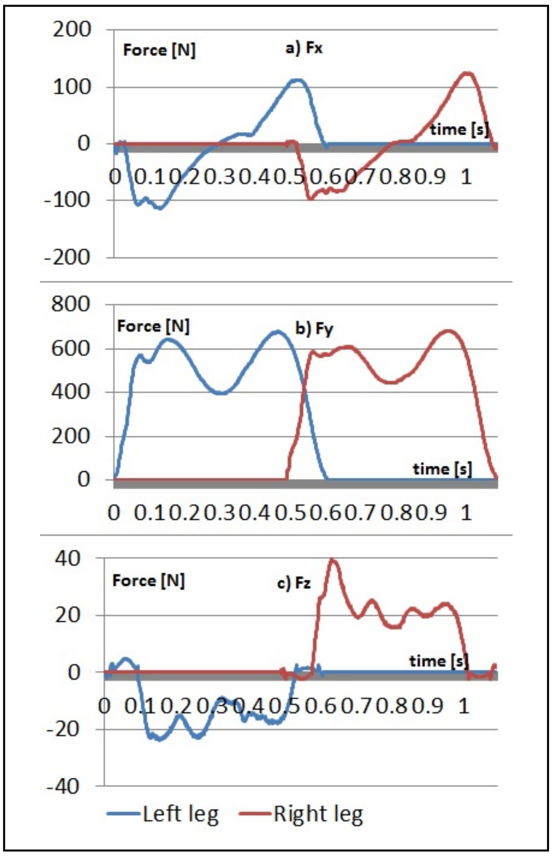

Fig. 2. The three components of GRF in: a) anterior/posterior, b) vertical and c) medial/lateral direction. The gait in sport shoes (the subject's body height 165.7 cm; body weight 61.3 kg, age 21 years).

In this work we compare particular components of the GRF for every lower limb individually after dividing them into sub phases. Taking ρ_{ij} as the distance between two time series of an *v –th* sub phase for a *l-th* lower limb, it has been calculated from the following equation:

$$\rho_{vl} = \sum_{m=1}^{M} DTW_m \qquad (1)$$

where: DTW_m – the cost of DTW between the same components of GRF of the same lower limb. M – the number of GRF components taken into account in determining the distance, in this work M=3 (three components for the lower limb).

Additionally, distances of DTW were determined for an entire gait stride with no division into sub-phases. In all, the difference in GRF from two different measurements was defined using nine distances: ρ_{L_LR}, ρ_{L_MidST}, ρ_{L_TSt}, ρ_{L_PreSw}, ρ_{R_LR}, ρ_{R_MidST}, ρ_{R_TSt}, ρ_{R_PreSw}, ρ_{Stride}. The L index indicates the left lower limb and the R index – the right one. According to [13] GRFs have not normalized to body weight.

E. Classification

The obtained distances as measurements of similarity of two GRFs causes that the natural choice is the k-nearest neighbours (kNN) classifier. The kNN classifier decides to assign the analysed object to one of the classes based on the affiliation to k classes of nearest neighbours. In the case of biometrics, it is best to set a threshold which would define the maximum possible distance in order to include the given neighbor. This will allow for a correct decision to be made also in cases when in the reasonable vicinity of the considered point in the characteristics area there are fewer points than k. Such approach was also applied in this paper. The threshold value was defined as:

$$\rho_{\vartheta_i} = \vartheta \quad \overline{\rho_i} \tag{2}$$

where: ϑ - arbitrarily chosen threshold; $\overline{\rho_i}$ - average distances between points (prototypes) belonging to the i-th class.

If the distance between the analysed instance and the i-th prototype was greater than the one determined in accordance to (2) it was assumed that this meant that the i-th prototype classified the analysed case to the NONE class. The classification was performed in accordance with the kNN algorithm – the highest number of occurrences decided the classification to one of the $N+1$ classes. This additional class - *NONE* was used in case of draws.

Due to the fact that after pre-processing there were 9 distances, it seemed only logical to utilise ensemble classifiers consisting of 9 kNN classifiers. In the work by [11] it was shown, however, that better results can be achieved when base classifiers are replaced by selectors of k nearest neighbours, and the decision of the whole classifier group will be made based on a weighted vote (weights based on rank order).

K labels of the nearest points are passed as selectors output. These labels are taken from a learning sequence with the right weight, the value of which depends on the obtained rank R in particular base classifier (selector of k nearest neighbors). The decision of the ensemble classifiers is a class label with the largest sum of weights.

$$cl = \arg\max\left(\sum_{j=1}^{9} w_j \cdot d_{j,i}\right) \tag{3}$$

where: cl - class label; k - number of neighbors, $w_j = [w_1, \ldots, w_R, \ldots, w_k]$ - weights, which are calculated from the following formula:

$$w_R = \frac{k+1-R}{k} \tag{4}$$

where: R – indicates the rank for j-th classifier, R={1, 2, …, k}; $d_{j,c}$ – decision of the j-th classifier, which indicates the k nearest neighbors, $d_{j,i} \in \{0,1\}$. If j-th classifier chooses class i then $d_{j,i}=1$ otherwise $d_{j,i}=0$.
The final decision is equal 'NONE' if at least two labels have the same sum of their weights or the obtained weighed sum in (3) is lower than assumed threshold Th.

III. Resuls and Disscussion

The study considers the following three scenarios:

a) The data contained the gait of people only in sports shoes;
b) The data in a learning series (possible prototypes) contained only gait in sports shoes, whereas the testing series contained all the remaining data (gait in both types of footwear);
c) The data in a learning series, as well as in testing series contains gait in both types of footwear.

In order to compare the obtained results with results from other authors the results will be presented for a varied number of randomly selected people from 10 to 80, every tenth person (i.e. 10, 20, 30, …,80). In order to minimise the randomness of the study, it was repeated for each number of person ten times. We take an mean value of this trials as a final result. The number of gait strides in a testing series was variable and depended on the number of people included in individual studies. In all cases both training set and testing one consisted mixed data ignoring time of the data recording (before or after breaks). Based on the results presented in [10] the number of considered k nearest neighbours was equal to 9. The results presented below (Tab. 1) assume the adoption of the most liberal strategy (Th=0).

TABLE I. CRR, FRR and FAR (%) Average values depending on the number of the subjects and used scenario

No. of sub.	**Scenario a)**			**Scenario b)**			**Scenario c)**		
	CCR	***FRR***	***FAR***	***CCR***	***FRR***	***FAR***	***CCR***	***FRR***	***FAR***
10	99.89	0	0.11	85.75	0.08	14.17	99.49	0.05	0.46
20	99.58	0	0.42	78.73	0.16	21.11	99.40	0.08	0.52
30	99.11	0	0.89	77.75	0.18	22.25	99.27	0.07	0.66
40	99.36	0.05	0.59	74.35	0.14	25.51	99.39	0.03	0.58
50	99.09	0.02	0.89	72.83	0.15	27.02	99.16	0.01	0.83
60	99.18	0.02	0.8	71.12	0.19	28.69	99.03	0.06	0.91
70	98.79	0.04	1.17	70.63	0.17	29.21	99.18	0.03	0.79
80	98.87	0.08	1.05	69.21	0.20	30.59	98.96	0.05	0.99

The adoption of the most liberal strategy caused the FRR value to be small and almost independent from the chosen scenario, as well as the number of people. It is easily noticeable that along with the increase in the number of people the CCR value drops, and the FAR value increases. In the case of scenarios a) and c) the change is slow, and in the case of b) it is very quick.

The high classification result was obtained for the a) scenario, when the studied people walked only in sports shoes. These results confirm the reports of other authors [20], that gait is a unique occurrence and can be used in biometrics. The results obtained here are worse than in the work by [10], where the data collection included also male gait. The presence of only women in a data group used in this work caused the group to be more homogenous and in turn harder to identify.

In the case of scenario b) the addition to the testing series of gait in footwear other than the one included in the learning series caused a decrease in the recognition quality. This confirms the suspicions of a significant change in a person's gait pattern depending on the footwear. The obtained results are significantly better than in the work by [15] and significantly worse than in the works by [6] and [5]. However, while comparing those results caution is advised, as for instance [6] took into account only men, and gait in male fashion footwear is not so different from sports shoes, which as shown in [15] influences the obtained classification results in a smaller degree. In turn in the work by [5] the testing series utilised data describing both women and men, however, there is no information on the percentage of women participating in this study, which makes it impossible to compare the results in a meaningful way. It is also worth noting that in two of the works other measurement systems were utilised: the motion capture system [15] and video cameras [5]. Similar signals were also considered in the work by [6] with the difference that the signals used there were also enriched with spatial features and signals derived from high-resolution sensing floor tile.

The comparison of the weighed sum (seen as an argument in (2)) with the chosen classification decision also seems interesting. In the case of correct classifications this value is relatively high, and in the case of FAR it is low. These values are respectively (average ± SD): 18.9 ± 9.76 and 6.95 ± 3.03. This also points to the fact that the intrasubject variability in many cases, even with the change of footwear, is significantly smaller than the intersubject variability.

The influence of experience in walking in high heels on classification was also analysed. In the case of women who more often wear sports shoes, the CCR was 71.20%, and in xthe case of women wearing high heels more often: 62.71%. This significant difference can serve as a statement that the frequency of wearing high heels influences the way of walking. A relatively higher CCR for subjects wearing sports shoes more often can point to a smaller, not permanent change in their gait pattern. It is worth noting that the CCR would be higher in this case if not for the fact that a few of the women walked clumsily, which could be clearly seen, as they wore high heels very seldom.

Regardless of the above mentioned analyses it needs to be stated that the practical usability of the biometrics system in the face of such a radical change of footwear and choosing the most liberal classification method is limited, even within a 10 person group. A solution which can reduce the FAR is setting the *Th* threshold at a reasonable level. The ROC curve showing the changes of classification is presented in fig. 3

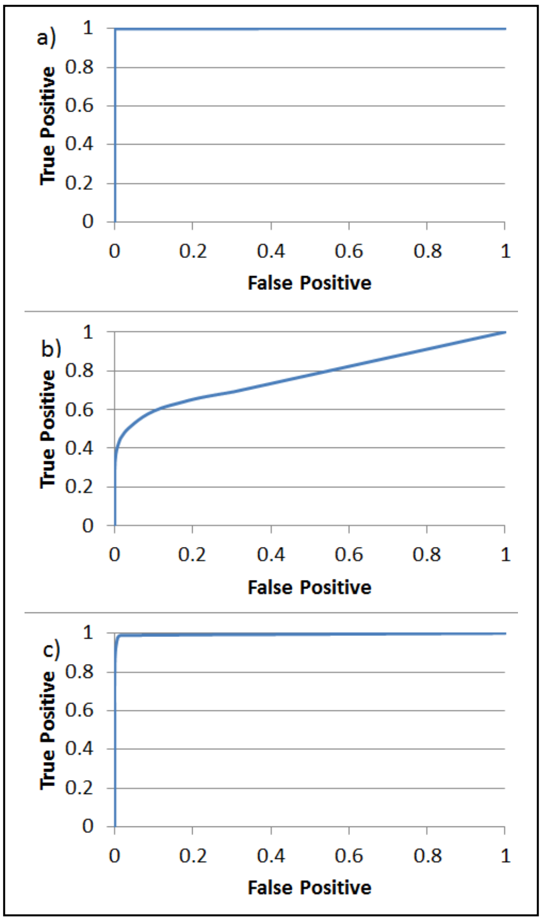

Fig. 3. The ROC curve in case of 80 subjects for scenario a) AUC=0.9997; b) AUC=0.7724; c) AUC= 0.9939

Scenario c) seems to offer some kind of a solution. The addition of high heeled gait to the learning data the CCR value improved significantly reaching a level comparable with scenario a). It needs to be stressed that those two scenarios cannot be seen as equal, as scenario a) included twice as many people. This is mostly due to the fact that some of the subjects walking in high heels were correctly recognized (often in 100%) also in the case of scenario b). Additionally, in the situation where the gait patterns in both types of footwear were relatively 'close' to each other, additional prototypes could overweigh the results of the vote. It should be underline that the possible areas for application of the scenario c) for biometric identification purposes is limited to the situations when we are able to collect gait data in both types of shoes (e.g. in offices, factories and other type of workplaces).

IV. Conclusions

In this article the operation of a biometrics system was tested depending on the footwear worn by females: sports shoes or high heels. It was shown that in the case where the high heeled gait is not in the learning series of a classifier group then the quality of the biometrics system is limited even with a small study group. The obtained results showed that in this case better results can be obtained for women who are not experienced in walking in high heels. A significant improvement of the quality of the biometrics system can be obtained by including in the learning series data describing the gait in both types of footwear. It needs to be stressed that the results point to a significant limitation in the biometrics of human gait for practical uses, limiting it to situations when we are able to obtain good measurement data both for sports shoes and high heels.

Further work in this subject should be conducted in two planes. First of all, the data should be expanded by data presenting the gait of men and women in various types of footwear. Additionally, such methods of feature extraction or classification should be found that would improve the results presented here.

Acknowledgment

This work was prepared within the frame of project (no. S/WM/1/2017) sponsored by Ministry of Science and Higher Education.

References

[1] M. Balazia and K.N. Plataniotis, "Human gait recognition from motion capture data in signature poses," IET Biometrics, vol. 6, no 2, 2017, pp. 129-137.

[2] Ch. J. Barton, J.A. Coyle and P. Tinley, "The effect of heel lifts on trunk muscle activation during gait: a study of young healthy females," J Electromyogr Kinesiol, vol 19, 2009, pp. 598-606.

[3] M.G. Blanchette, J.R. Brault and C.M. Powers, "The influence of heel height on utilized coefficient of friction during walking," Gait & posture, vol.34, no. 1, 2011, pp. 107-110.

[4] F.M. Castro, M.J. Marín-Jiménez and N. Guil, "Multimodal features fusion for gait, gender and shoes recognition," Machine Vision and Applications, vol. 27 no. 8, 2016, pp.1213-1228.

[5] T. Connie, M. Goh, T.S. Ong, H.L. Toussi and A.B.J. Teoh, "A challenging gait database for office surveillance," in Image and Signal Processing (CISP), 2013 6th International Congress on, IEEE, vol. 3, pp. 1670-1675, Dec 2013.

[6] P.C. Connor, "Comparing and combining underfoot pressure features for shod and unshod gait biometrics," in Technologies for Homeland Security (HST), 2015 IEEE International Symposium on, IEEE, pp. 1-7 Apr 2015.

[7] N.J. Cronin, "The effects of high heeled shoes on female gait: a review," J Electromyogr Kinesiol, vol. 24, 2014, pp. 258-263.

[8] M. De Marsico and A. Mecca "Biometric walk recognizer," in International Conference on Image Analysis and Processing, pp. 19-26, Springer International Publishing, Sept 2015.

[9] P. A. de Oliveira Pezzan, S.M.A. João, A.P. Ribeiro, and E.F. Manfio, "Postural assessment of lumbar lordosis and pelvic alignment angles in adolescent users and nonusers of high-heeled shoes," J Manip Physiol Ther," vol. 34, no. 9, 2011, pp. 614-621.

[10] M. Derlatka, and M. Bogdan, "Combining Homogeneous Base Classifiers to Improve the Accuracy of Biometric Systems Based on Ground Reaction Forces," J Med Imaging Health Inform, vol. 5, no. 8, 2015, pp. 1674-1679.

[11] M. Derlatka, and M. Bogdan, "Ensemble kNN classifiers for human gait recognition based on ground reaction forces," in: Human System Interactions (HSI), 8th International Conference on, IEEE, pp. 88-93, Jun 2015.

[12] D. Gafurov, P. Bours and E. Snekkenes, "User authentication based on foot motion," SIViP, vol. 5, iss. 4, pp. 457-467, Nov. 2011.

[13] J. Jenkins and C. Ellis, "Using ground reaction forces from gait analysis: body mass as a weak biometrics," in: Pervasive Computing, eds. A. LaMarca et al., LNCS, Science Springer Berlin Heidelberg, vol. 4480, pp. 251-267, May 2007.

[14] R. Katiyar, V.K. Pathak, K.V. Arya, "A study on existing gait biometrics approaches and challenges,". Int. J. Comp. Sci., Vol. 10, no 1, 2013, pp. 135-144.

[15] M. Kim, M. Kim, S. Park, J. Kwon, and J. Park, "Feasibility Study of Gait Recognition Using Points in Three-Dimensional Space," Int J Fuzzy Log Intell Syst, vol. 13, no. 2, 2013, pp.124-132.

[16] J. Man, J. and B. Bhanu, "Individual recognition using gait energy image," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 2, 2006, pp. 316-322.

[17] J. Mantyjarvi, M. Lindholm, E. Vildjiounaite, S.M. Makela, and H.A. Ailisto, "Identifying users of portable devices from gait pattern with accelerometers," in International Conference on Acoustics, Speech, and Signal Processing, Proceedings (ICASSP'05), IEEE, vol. 2, pp. 973-976, March 2005.

[18] M. Milovanovic, M. Minovic, D. Starcevic, "Walking in colors: human gait recognition using Kinect and CBIR," IEEE MultiMedia Mag., vol. 20, no. 4, 2013, pp. 28-36.

[19] S. P. Moustakidis, J. B. Theocharis and G. Giakas, "Feature extraction based on a fuzzy complementary criterion for gait recognition using GRF signals," Control & Automation. IEEE 17th Mediterranean Conference on, pp. 1456-1461, 2009.

[20] T. C. Pataky, T. Mu, K. Bosch, D. Rosenbaum and J.Y. Goulermas, "Gait recognition: highly unique dynamic plantar pressure patterns among 104 individuals," J. R. Soc. Interface vol. 9, no. 69, 2011, pp. 790-800.

[21] E.B. Simonsen, M.B. Svendsen, A. Norreslet, H.K. Baldvinsson, T. Heilskov-Hansen, P.K. Larsen, T. Alkjær and M. Henriksen, "Walking on high heels changes muscle activity and the dynamics of human walking significantly," J Appl Biomech, vol. 28 no. 1, 2012, pp. 20-28.

[22] S.X. Yang, P.K. Larsen, T. Alkjær, E.B. Simonsen and N. Lynnerup, "Variability and similarity of gait as evaluated by joint angles: implications for forensic gait analysis,", Journal of Forensic Sciences, vol. 59 no. 2, 2014, pp. 494-504.

[23] JH Yoo and M. S. Nixon, "Automated markerless analysis of human gait motion for recognition and classification," Etri Journal, vol. 33, no. 2, 2011, pp. 259-266.

[24] J. Yun, "User identification using gait patterns on UbiFloorII," Sensors vol. 11, no. 3, 2011, pp. 2611-2639.