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RECOGNITION OF HUMAN GAIT BASED ON GROUND REACTION FORCES AND COMBINED DATA FROM TWO GAIT LABORATORIES

Marcin DERLATKA*, Maria SKUBLEWSKA-PASZKOWSKA, Paweł POWROŹNIK**, Jakub SMOŁKA**, Edyta ŁUKASIK**, Agnieszka BORYSIEWICZ***, Piotr BORKOWSKI*, Dariusz CZERWIŃSKI******

*Institute of Biomedical Engineering, Faculty of Mechanical Engineering, Bialystok University of Technology, Wiejska 45C, 15-351 Bialystok, Poland
** Department of Computer Science, Faculty of Electrical Engineering and Computer Science Lublin University of Technology, Nadbystrzycka 36B, 20-618 Lublin, Poland
*** Department of Emergency Medicine, Faculty of Health Sciences, Medical University of Białystok, Szpitalna 37, 15-295 Bialystok, Poland
**** Department of Applied Computer Science, Faculty of Mathematics and Information Technology, Lublin University of Technology, Nadbystrzycka 38B, 20-618 Lublin, Poland

m.derlatka@pb.edu.pl, maria.paszkowska@pollub.pl, p.powroznik@pollub.pl, jakub.smolka@pollub.pl, e.lukasik@pollub.pl, agnieszka.borysiewicz@umb.edu.pl, p.borkowski@pb.edu.pl, d.czerwinski@pollub.pl

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Abstract: In a world in which biometric systems are used more and more often within our surroundings while the number of publications related to this topic grows, the issue of access to databases containing information that can be used by creators of such systems becomes important. These types of databases, compiled as a result of research conducted by leading centres, are made available to people who are interested in them. However, the potential combination of data from different centres may be problematic. The aim of the present work is the verification of whether the utilisation of the same research procedure in studies carried out on research groups having similar characteristics but at two different centres will result in databases that may be used to recognise a person based on Ground Reaction Forces (GRF). Studies conducted for the needs of this paper were performed at the Bialystok University of Technology (BUT) and Lublin University of Technology (LUT). In all, the study sample consisted of 366 people allowing the recording of 6,198 human gait cycles. Based on obtained GRF data, a set of features describing human gait was compiled which was then used to test a system's ability to identify a person on its basis. The obtained percentage of correct identifications, 99.46% for BUT, 100% for LUT and 99.5% for a mixed set of data demonstrates a very high quality of features and algorithms utilised for classification. A more detailed analysis of erroneous classifications has shown that mistakes occur most often between people who were tested at the same laboratory. Completed statistical analysis of select attributes revealed that there are statistically significant differences between values attained at different laboratories.

Key words: human gait recognition, biometrics, ground reaction forces, databases.

1. BACKGROUND

Nowadays, in a world that has become more and more digital, the fast, correct identification of a user, granting him access to his resources including documents, photos, films, or even money, becomes quite significant. At the same time, various biometric features such as fingerprints [1], eye movement [2], voice [3], keystroke [4], face [5], gait [6] or a combination of two or more of such features [7, 8] are more frequently utilised as a tool of such recognition.

Among the biometrics mentioned, human gait is drawing increasing attention [9, 10]. This is caused by its unique characteristics. The human gait is the most complex activity performed subconsciously by a person. It is accepted that after maturity, the way a human being walks remains unchanging and is characteristic of that particular person. What is more, its measurement is possible without any type of unnatural interaction between the considered person and the measuring device.

It should be noted that reliable identifications require statistical accuracy including data of sufficient quantity and quality. It is for this reason that numerous laboratories all around the world concerned with the biomechanics of human gait have compiled many databases containing biometric samples [11–13]. These databases were then made available to researchers to support their efforts related to the search for the optimal human recognition algorithms. Such databases also include values of attributes concerning human gait, with the number of people from whom the data was obtained ranging from few to several thousand (OULP-Age). Unfortunately, these databases are rarely compatible. This is mainly caused by differing measurement values describing human gait. These indexes most often contain data that:

– has been recorded by video cameras [14],
– is accelerometer and gyroscope data collected from inertial measurement units or mobile devices [15],
– describes ground reaction forces (GRF) registered by force plates [12].

Additionally, some databases contain data that illustrates situations that are problematic for human gait recognition algorithms such as people walking while doing different activities [16], in the

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wild [17], at different speeds and wearing varying clothing [13], with or without a bag [18], seen from various viewing angles [19], on different surfaces [20] or in various shoe types [12].

Another potential problem concerns the utilisation of measuring systems for gathering data having varying characteristics including differing sampling frequency or performing measurements under diverse conditions resulting in the acquisition of data that differs significantly. Differences in force plate levelling are also a source of slight differences in results. Smith and Ditroilo [21] analysed ground reaction force values under conditions when the force plates were either bare or covered by three varying materials including vinyl, sportflex and astroturf. Statistical analysis showed that covering material had a significant impact on peak force and rate of force development measurements during a testing procedure.

As mentioned earlier, the databases are primarily used to build biometric systems characterised by the highest possible quality, understood as the accuracy of human recognition. The main part of every biometric system is a module that assigns a particular biometric signature to one of the people represented within the database. This assignment is realised using classifiers. Thus, the search for classification algorithms and features that describe a person's physical characteristics or behaviour is a large part of work in the biometrics field.

Horst et al. [22] make human gait recognition based on GRF and three publicly available datasets. For the experiments, they utilised subsets of the AIST Gait Database, the GaitRec dataset, and the Gutenberg Gait Database. It should be emphasised that the main aim of their work was demonstrating the uniqueness of gait signatures and highlighting the gait characteristics that are most distinctive of each person. The problem of the integrity of the data contained in different databases and its impact on the quality of classification of the combined sets was not analysed in this work.

According to the author's knowledge within the literature there are no works that could indicate whether the combination of data gathered by various gait laboratories allows a relatively problem-free expansion of a database. The present work aims to verify if adherence to the same research procedure in a study carried out on a similar sample group at two different research centres will result in the compilation of databases that can be used for human recognition based on GRFs.

2. MATERIAL AND METHODS

Research was carried out at two human gait biomechanics laboratories: the Institute of Biomedical Engineering of the Bialystok University of Technology (BUT) and the Department of Computer Science of the Lublin University of Technology (LUT). Testing paths at both labs were of similar length with measurements made at BUT performed using two Kistler-made, 60 cm × 40 cm force plates registering data with a frequency of 960 Hz. GRF registration at LUT occurred through the utilisation of two 60 cm × 40 cm force plates manufactured by AMTI, model no. BP400600-4000, which recorded data with a frequency of 1,000 Hz (Fig. 1). To eliminate the largest number of factors that may have an impact on the results of performed measurements, the tests were carried out in accordance with the same procedure and under the supervision of the same person, the first author of the present work.

Fig. 1. Image of the LUT testing path with two AMTI-manufactured force plates indicated in the foreground. LUT, Lublin University of Technology

2.1. The study group

The study conducted at BUT was carried out with the participation of 322 people including 139 women and 183 men while that realised at LUT involved 14 people including 4 women and 10 men. Data concerning both groups has been presented in Tab. 1.

Tab. 1. Characteristics of people comprising groups of study participants

	Age (years ± SD)	Body height (cm ± SD)	Body weight (kg ± SD)
BUT	21.54 ± 1.17	175.01 ± 9.59	74.59 ± 16.74
LUT	22.36 ± 1.01	175.07 ± 9.59	70.02 ± 13.86

BUT, Bialystok University of Technology; LUT, Lublin University of Technology.

Prior to the initiation of measurements, every person taking part in the study, regardless of whether they were tested at BUT or LUT, was informed about the aim and course of the testing and signed appropriate authorisations. Next, the participants were asked to walk at their own pace through the testing path containing two hidden force plates. The test was initiated by the person conducting the research. In cases where the participant did not clearly hit into both platforms, their starting point was slightly corrected. Every person walked through the testing path numerous times wearing their own sports shoes. To prevent fatigue, 1–2 min rest was conducted after every 10 passes through the path. In total, during the study, 5,980 gait cycles were recorded at BUT and 218 at LUT. The study was conducted in accordance with the Declaration of Helsinki, and approved by the Bioethics Committee of Regional Medical Chamber in Bialystok (no 18/2006, 8 November 2006) and the Bioethics Committee of Medical University of Bialystok (no. APK.002.192.2022, 28 April 2022, and no. APK.002.251.2023, 20 April 2023).

2.2. Calculating of features

GRFs gained by individual force plates consisted of three components: vertical, medial/lateral and anterior/posterior. The values of the vertical component of GRF attained at LUT, in com-

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parison to those gathered at BUT, were negative, therefore, to standardise measurement data, Fy values from LUT were negated (Fig. 2). Registered GRFs were presented using time series x1, x2, ..., xN, where N is the number of samples. Generally, the duration time of the support phase of a person's gait depends on several factors and varies so N is variable. To minimise the impact of the duration of the support phase and facilitate the comparison of two distinct gait cycles, parameter values were calculated using formulas (1)–(7).

The features describing gait were selected on the results reported in the work [23]:

– Mean of the signal:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i = \frac{x_1+x_2+\dots+x_N}{N} \tag{1}$$

– Variance of the signal:

$$var = \frac{1}{N}\sum_{i=1}^{N}|x_i - \bar{x}|^2 \tag{2}$$

– Standard deviation of the signal:

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{3}$$

– Peak-to-peak (ptp) amplitude of the signal:

$$ptp = (\max(x) - \min(x)) \tag{4}$$

where x is the signal-set containing the values of time series x1, x2, ..., xN, of a given lower limb and a given GRF component.

– Skewness of the signal is computed as the Fisher-Pearson coefficient of skewness:

$$skew = \frac{m_3}{m_2^{3/2}} \tag{5}$$

where $\mathrm{m_i} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{x_i} - \bar{\mathrm{x}})^{\mathrm{k}}$ the biased kth sample central moment

– Kurtosis of the signal:

$$kurtosis = \frac{m_4}{var^2} \tag{6}$$

– Hurst exponent of the signal is calculated from the rescaled range and averaged over all the partial time series of length N:

$$\left(\frac{R}{SD}\right)_t = \frac{R_t}{SD_t} \tag{7}$$

where R/SD is averaged over the regions *[x_1,x_t],[x_{t+1},x_{2t}]* until *[$x_{(l-1)t+1}$,x_{lt}]* where *l=floor(N/t)*, *t* = 1,2,...,*N*, *R* is the range of series, *SD* standard deviation of series. Hurst exponent is defined as the slope of the least-squares regression line going through a cloud of partial time series [16].

It is also necessary to specify that signal features were calculated independently for each component of GRF and separately for each lower limb. Thus, created input space consisted of a total of 42 parameters. Since the values of obtained parameters vary significantly from one another it becomes necessary to standardize them before classification using the following equation:

$$x_{std} = \frac{x_{old} - \overline{x_{old}}}{SD} \tag{8}$$

where:

$\overline{x_{old}}$ - mean of the *j*-th feature value before standardisation;

x_{old} - single value of the *j*-th feature value before standardisation.

It should be stressed that the standardisation of data was carried out separately for every utilised data set (only BUT, only LUT, BUT + LUT).

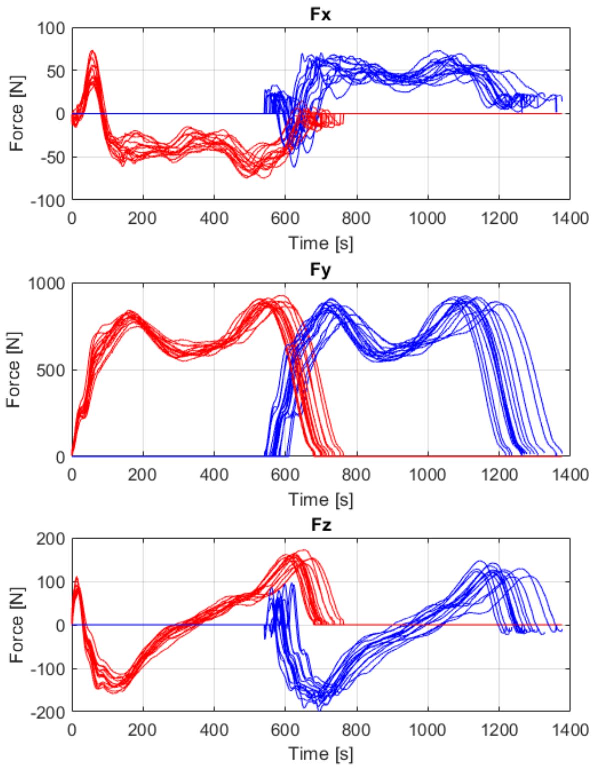

Fig. 2. Components of GRF in: medial/lateral—Fx; vertical—Fy (negated); anterior/posterior—Fz direction of the left lower limb (blue line) and of the right one (red line) in sports shoes. The graph shows a dozen steps of a man aged 23 years with a weight of 82.2 kg and height of 178 cm recorded on the LUT. GRF, ground reaction forces; LUT, Lublin University of Technology

2.3. Classification algorithms

Within the presented solution, it had been decided to test several well-known algorithms. Among them were: k nearest neighbors (kNN) classifier, naive Bayes (NB), feedforward neural network with no more than two hidden layers (MLP), Classification and Regression Tree (CART), support vector machines (svm), regularised linear discriminant analysis (rLDA) and Adam Deep Learning Optimization Algorithm (deep ANN). The feedforward neural network consisted of one or two hidden layers with relu or tanh activation functions. The output (classification) layer used the softmax activation function. The number of inputs was always equal to 42 and the number of outputs was equal to the number of classes. MLP used Broyden–Fletcher–Goldfarb–Shanno quasi-Newton algorithm for learning.

The employed deep neural network consisted of the following seven layers:

– feature input layer (42 inputs);
– dense layer with 400 neurons;
– batch normalisation layer;
– relu layer;

- dense layer with the number of neurons equal to the number of classes;
- softmax layer;
- classification layer.

A more detailed description of the working of individual algorithms may be found in literature including, for example, [23–25].

Every classifier was trained for a group of features listed in subsection 2.2 using 10 folds of cross-validation. Each time, the same division of data into folds was utilised, thanks to which results obtained by different classifiers were comparable. The quality of every classifier was determined by its accuracy. This represents the proportion of true positive results (both true positive as well as true negative) in the selected population.

$$\text{Accuracy} = \frac{\text{TruePositive+TrueNegative}}{\text{Number of classified data}} \tag{9}$$

The number of classes equalled the number of people being recognised and, of course, differed depending on the data set being utilised. All data processing and analysis were performed using MATLAB 2023a software.

3. RESULTS AND DISCUSSION

Tab. 2 presents the accuracy results for individual classifiers. It must be stressed that these results are the product of having conducted several learning cycles allowing the optimisation of parameters specific to particular classification algorithms. Tab. 2 contains the best-obtained results.

Tab. 2. Results of person identification depending on the utilised classifier and data set

	BUT	LUT	BUT + LUT
kNN	96.76%	99.08%	96.90%
NB	96.07%	97.52%	96.11%
MLP	93.14%	98.62%	92.80%
CART	72.66%	83.94%	72.81%
SVM	89.85%	98.62%	90.03%
rLDA	99.46%	100%	99.52%
deep ANN	96.79%	98.18%	96.93%

BUT, Bialystok University of Technology; CART, classification and regression tree; kNN, k nearest neighbors; naïve Bayes (NB); feedforward neural network (MLP); support vector machines (svm); deep artificial neural network (deep ANN); LUT, Lublin University of Technology; rLDA, regularised linear discriminant analysis.

The results displayed in Tab. 2 indicate that all classifiers except for decision tree (CART), cope well or very well with the task of identifying a particular person. The highest values, reaching >99.45%, were obtained with the rLDA algorithm and are reflected in the study results [23]. In the paper [22], the worst result of classification, as here, was obtained using CART. In contrast to our results in the paper [22], SVM classifier did the best job, allowing a correct recognition in >99.3% of cases. This result is only slightly lower than the best score presented in Tab. 2, however it was obtained for a larger group of people.

It is easy to see that the best results were attained with relation to the LUT data set while the worst were seen for the BUT data set. Undoubtedly, this is connected with the number of study participants and, as has been shown, for example, in paper [26], a rise in the number of identified people causes a gradual yet unavoidable fall in the percentage of correct identifications. Therefore, to be able to directly compare recognition results for both the BUT and LUT sets, 14 people were randomly drawn 10 times from the BUT set and the table presents the average classifier accuracy results for both BUT and LUT with 10-fold cross-validation also being used in this case (Tab. 3). The direct comparison shows that in case of human gait recognition based on samples consisting of 14 people the accuracy for the BUT database is only slightly higher than the for LUT database. The biggest differences are for NB and CART classifiers. It should be noted that in all other classifiers, the accuracy of recognising individuals from the LUT database is within the range for the BUT database given in Tab. 3.

Tab. 3. Person identification results depending on the classifier used for the database containing 14 people from the BUT data set

	BUT (14 person)	Standard deviation	Range <min-max>
kNN	99.70%	0.377	98.94%–100%
NB	99.43%	0.491	98.45%–100%
MLP	98.70%	0.614	97.89%–99.62%
CART	93.08%	2.905	87.21%–96.88%
SVM	99.24%	0.573	98.45%–100%
rLDA	99.93%	0.154	99.63%–100%
deep ANN	98.94%	0.550	97.73%–99.64%

BUT, Bialystok University of Technology; CART, classification and regres-sion tree; kNN, k nearest neighbors; naïve Bayes (NB); feedforward neural network (MLP); support vector machines (svm); deep artificial neural network (deep ANN); rLDA, regular-ised linear discriminant analysis.

Looking at Tab. 2, it was noted that the results for all classifiers except MLP for the combined set (BUT + LUT) are slightly higher than just for BUT. Since, according to the previous statement, they should be rather slightly worse, this could mean that features established for the LUT data set assume different values than for the BUT data set. In that case, there will be no increase in the number of classes in the same place of the feature space, since the data from the two labs is far enough apart. Therefore, the classification of data from the LUT set will provide very good results (see Tab. 2), and since for both BUT + LUT sets, there will be more correctly classified instances then accuracy will slightly increase.

Tab. 4. Number (and percentage) of errors in the identification of people with relation to the laboratory at which, in reality, those people were tested occurring in classifications using deep ANN

		Predicted research centre	
		BUT	**LUT**
Actual research centre	**BUT**	182 (3.04%)	1 (0.02%)
	LUT	1 (0.46%)	5 (2.29%)

BUT, Bialystok University of Technology; LUT, Lublin University of Technology.

For this reason, the tables below present a specific form of a confusion matrix that shows whether incorrect identifications concern people who were tested at the same or at different laboratories. Incorrect recognitions made by the most accurate classifier rLDA (Tab. 5) and, to better illustrate the phenomenon, a somewhat less precise, in this case, deep ANN classifier (Tab 4), were chosen for the tables. Even a cursory analysis of values presented in the tables allows the conclusion that the errors are mostly made with respect to people who were tested at the same laboratory. Erroneous identifications for people who were tested at different centres, on the other hand, are, literally, singular occurrences.

Tab. 5. Number (and percentage) of errors in the identification of people with relation to the laboratory at which, in reality, those people were tested occurring in classifications using rLDA

		Predicted research centre	
		BUT	**LUT**
Actual research centre	**BUT**	29 (0.48%)	0 (0.00%)
	LUT	0 (0.00%)	1 (0.02%)

BUT, Bialystok University of Technology; LUT, Lublin University of Technology.

Tab. 6. The average and standard deviation for the mean of the signal as well as the amplitude peak-to-peak features attained for both lower extremities as well as for both laboratories

	Feature	**Average (N/(kg·m/s²))**	**SD**
BUT	Mean_Left_Fy	0.4301	0.0101
	Mean_Right_Fy	0.4435	0.0101
	P2p_Left_Fy	1.1415	0.0665
	P2p_Right_Fy	1.1652	0.0641
	Mean_Left_Fz	0.0002	0.0047
	Mean_Right_Fz	0.0008	0.0042
	P2p_Left_Fz	0.3811	0.0702
	P2p_Right_Fz	0.4171	0.0613
LUT	Mean_Left_Fy	0.4414	0.0142
	Mean_Right_Fy	0.4444	0.0160
	P2p_Left_Fy	1.1291	0.0574
	P2p_Right_Fy	1.1377	0.0643
	Mean_Left_Fz	0.0089	0.0044
	Mean_Right_Fz	–0.0151	0.0069
	P2p_Left_Fz	0.3834	0.0558
	P2p_Right_Fz	0.3886	0.0573

BUT, Bialystok University of Technology; LUT, Lublin University of Technology.

To further verify differences between data statistical tests were performed with four characteristics from every data set being selected. These were mean and p2p values of anterior-posterior and vertical components of GRF for both lower limbs calculated according to formulas (1) and (4), respectively. In contrast to values of features utilised to train classifiers, this time these values were normalised for the body mass of the person, a standard procedure used in human gait biomechanics allowing the comparison of GRFs gathered from people whose body weight differs. Parameters calculated on the basis of Fy and Fz were selected since it has been shown that the medial-lateral component has the smallest impact on human recognition [27]. The mean and standard deviation values of these features have been presented in Tab. 6.

The verification of the hypothesis that appropriate parameters measured at different laboratories vary from one another was carried out using the Statistica software. Based on the Central Limit Theorem and sample cardinality obtained in both labs, it was accepted that the attributes described by the present work exhibit normal distribution. Since the number of samples gathered at individual laboratories differed significantly the Welch test was utilised to demonstrate a statistically significant difference between the values recorded at BUT in relation to those calculated on the basis of measurements performed at LUT. The values of these tests attained during the verification of the hypotheses as to a lack of statistically significant differences have been presented in Tab. 7. Statistically significant values have been marked in red.

Tab. 7. Welch test *p*-level values

Feature	**Welch test *p*-level**	**Feature**	**Welch test *p*-level**
Mean_Left_Fy	<0.001	Mean_Right_Fy	0.409
P2p_Left_Fy	0.002	P2p_Right_Fy	<0.001
Mean_Left_Fz	<0.001	Mean_Right_Fz	<0.001
P2p_Left_Fz	0.002	P2p_Right_Fz	<0.001

Results of statistical tests indicate that statistically significant differences at levels of $p < 0.05$ do not occur solely with the mean value of the right leg vertical component. Through this, the results presented in Tabs 4 and 5 are verified and confirm the existence of significant differences between measurements done at the two research centres. It is worth mentioning that the cause of these differences may be found in the fact that the force plates were manufactured by different companies as well as in the level of force inhibition of the material used to cover them [21]. Another, although less likely, possible cause for differing results is that the samples consisted of different people, each with a characteristic manner of gait. Thus, an interesting question arises, one unanswered by the present work, whether the results would be different if the tests were conducted on the same group of people at both research centres. The answer would ultimately confirm the thesis concerning the differences between laboratories.

5. CONCLUSION

The paper presents the working of a biometric system for the recognition of a person based on their gait. Test data was recorded at two biomechanics human gait laboratories. Generally, the obtained human identification results were very good and confirmed the great potential of human gait as a biometric measure. An analysis of errors, enriched with statistical analysis, showed that the specific character of a given laboratory may significantly impact the results of measurements. It turned out that even with the utilisation of the same procedure and with the same personnel conducting the tests the final results may differ, with the conclusion being that the combining of databases compiled by different sources does not have to result in better data allowing the creation of a biometric system that is, for example, more resistant to external factors.

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Marcin Derlatka: https://orcid.org/0000-0002-6736-5106

Maria Skublewska-Paszkowska: https://orcid.org/0000-0002-0760-7126

Paweł Powroźnik: https://orcid.org/0000-0002-5705-4785

Jakub Smołka: https://orcid.org/0000-0002-8350-2537

Edyta Łukasik: https://orcid.org/0000-0003-3644-9769

Agnieszka Borysiewicz: https://orcid.org/0000-0001-7740-7800

Piotr Borkowski: https://orcid.org/0000-0001-9038-2601

Dariusz Czerwiński https://orcid.org/0000-0002-3642-1929