Gait Feature Analysis of Polyneuropathy Patients

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***Abstract*—Polyneuropathy (PNP) and aging both bring changes to the walking pattern of elderly people. However, the identification methods of PNP from gait patterns were not sufficiently investigated from a technical perspective. In this study an automated classification method was developed to discriminate the neuropathic gait from both young healthy and old healthy gait using artificial neural network (ANN). A robust markerless gait detection system was employed and experiments were conducted in normal clinical conditions on 10 young, 10 old and 10 neuropathy patients. Four types of gait features, namely temporal features, kinematic joint trajectories in time domain, the Fourier transform of joint angles in frequency domain, and the symmetry indexes, were extracted. One-way analysis of variance (ANOVA) was employed as a statistical analysis tool and feature selection method. Each type of features and the selected features obtained from ANOVA were served as the input of a two-layer-feed-forward neural network separately. A two-fold cross validation method with enhanced generalization was utilized to evaluate the accuracy of classification. The ground truth information for the result validation was provided by the medical experts involved in the study. The outcome of individual feature set showed that the kinematic features in time domain reached the highest classification accuracies of 94.2%, 94.8% and 94.8% for three classes, while the symmetric features yielded the lowest. Combining two sets of features can improve the performance slightly and the best performance was achieved by using the selected significant features with accuracies of 96.2%, 97.0% and 96.9% respectively.**

Keywords— artificial neural network; classification; gait patterns; polyneuropathy; statistical analysis

I. INTRODUCTION

Gait analysis or assessment is the systematic study of human walking, which is used in the early detection, medical treatment and rehabilitation of those diseases that affect the locomotor system [1]. The analysis is usually applied to clinical research by comparing the subject's data with an age appropriate healthy database to identify abnormalities and impairment severity [2]. Gait variables extracted from temporal-spatial measurements (e.g. stride time, walking speed, stance time), the symmetry indexes between two lower limbs, and kinematic parameters such as hip and knee joint angles have been widely used to identify key characteristics of neurodegenerative diseases.

Polyneuropathy (PNP) or peripheral neuropathy is a disease that systemically affects peripheral nerves and results in reduced feedback control of locomotion. The neuropathic gait is regularly defined as a type of steppage gait with foot drop caused by the weakness of foot dorsiflexion [3]. Several previous studies have been conducted on neuropathic gait and showed that the PNP patients walk with shorter stride length, longer stride time, prolonged double support time, increased gait variability and smaller hip range of motion (ROM) in sagittal plane [4-7]. However, most of these studies examined the gait pattern only under laboratory situation, where the walking pattern could be significantly influenced by the doctors' instructions and complex experimental setups. Besides, polyneuropathy is a disease commonly seen among the elderly. Clinical research has indicated that aging by itself has impacts on gait patterns including increased stride rate [8], smaller minimum toe clearance [9], longer standing period [10], decreased foot range of motion [11] and increased walking instability [12]. Due to the high incidence of polyneuropathies among the elderly, it is currently not clear which changes are caused by normal aging and which by PNP. Therefore, a more comprehensive comparison which invokes both age-matched healthy subjects and young healthy subjects is necessary.

In order to obtain the data required for the computer-based gait analysis, marker-based gait capture systems have been used during the last few decades [13]. These systems relay primarily on markers or sensors attached at defined locations on the human body and therefore can be highly expensive, with high complexity and invasive to patients. As in this study we aim at investigation of the gait patterns in a standard room condition with simple setups, a robust markerless vision-based system was employed [14]. Basic temporal parameters and kinematic joint angles of hip and knee in sagittal plane can be obtained from the above system.

Artificial neural networks (ANN) were found to be one of the most prevalent methodologies for gait analysis in the recent years [15]. ANN is a statistical machine learning model used for decision making and pattern recognition and proved to be more effective than biomechanical methods or conventional statistics [16]. Numerous researches have been done by applying ANN as a classifier to identify abnormal gait patterns. For instance, Jaime et al [17] trained a multilayer perceptron ANN and reached a performance of 95% on the diagnosis of Alzheimer's disease with 21 patients and 21 control subjects. Wu [18] proposed a new wavelet-based feature extraction technique and tested it with an ANN classifier on 24 healthy young and 24 healthy elderly subjects. The results indicated that the ANN classifier can be used as an effective tool for evaluating the normal gait changes of aging. Further, the ground reaction force and wavelet-based features were served as the input of the ANN in another study to classify healthy and pathological gait and yielded a classification accuracy of 95%

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[15]. In addition, patients with Parkinson's disease were also classified successfully using four significant features, namely, step length, walking speed, knee angle and ground reaction force, with a multilayer perception ANN [19]. Although many works have been done on the recognition of neurodegenerative gait, none of them applied machine learning algorithms to neuropathic gait and the detailed clinical gait features of neuropathies were not yet discussed in the technical research community.

The objective of this study is to investigate different types of gait features of elderly people with and without polyneuropathy in real-life and standard room environment, by using statistical method and ANN. In future the results will be used to support medical doctors in early diagnosis of PNP and in evaluation of medical treatments. The examined features consist of basic temporal features, hip and knee kinematic features extracted in both time and frequency domain, and the symmetry indexes between two legs. Particularly, one additional group, the young healthy group, was added to this study to evaluate and compare the changes caused by aging and PNP. The performance of the algorithms developed in the paper was validated based on ground truth values provided by the medical personnel using markerless vision system for data acquisition.

II. METHODLOGY

A. Participants

This study was carried out by the Institute of Automation (IAT) of University of Bremen and supported by the BAG Prof. Spranger, Dr. Berg. Thirty subjects were recruited in this study: ten young healthy subjects, ten old healthy subjects, and ten subjects with PNP. All patients with PNP were diagnosed by the medical doctors and had no other diseases. All participants were assigned into one of the three groups and labeled with Young, Old and PNP accordingly. TABLE I illustrates the physical characteristics of these three groups of subjects.

B. Data Acquisition Using Markerless Vision-Based System

Reha@home [14], a robust markerless vision-based gait capture system was used in the research to acquire the gait measurements. The system employs a RGBD camera and is capable of capturing the temporal and kinematic pattern of the human waking in the sagittal plane in clustering environment. The performance of the system was evaluated with an electrogoniometer and proved that the accuracy fulfills the clinical requirements. During the test, the camera of the system was mounted firmly on a tripod and all participants were requested to and walk four times in front of the camera in a straight line from left to right and four times from right to left with self-preferred speed.

TABLE I. PHYSICAL CHARACTERISTICS OF THREE GROUPS OF SUBJECTS. (F: FEMALE, M: MALE, SD: STANDARD DEVIATION)

Group	Gender		Age(years)		Mass(kg)		Height(cm)	
	M	*F*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Young	7	3	26	5.7	68.8	10.1	174.2	7.2
Old	6	4	63	12.3	82.1	9.6	177.3	6.6
PNP	7	3	70	13.3	86.3	13.4	176.8	5.4

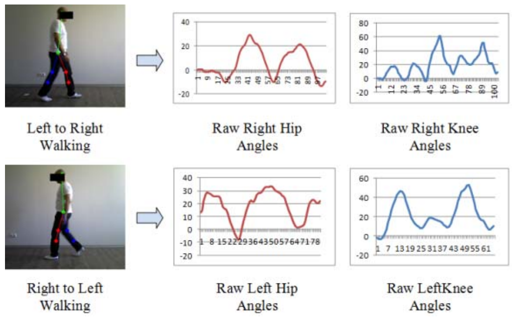

Fig. 1. Gait detection results of one subject using Reha@home system. The temporal parameters as well as hip and knee joint angles were captured.

The sampling frequency of the system is 30 Hz and the distance between the walkway and the camera is approx. 2.5 meters. Next, these entire recordings were observed by the therapists and the most representative trials were selected for both walking directions for each subject. The selected videos were processed using the Reha@home system. The detection result of this system on one subject is depicted in Fig.1.

C. Pre-processing

The pre-processing of the data analysis roughly discussed in this section contains following steps: gait cycle segmentation, missing data interpolation and joint trajectory normalization.

1) Gait Cycle Segmentation:

A complete gait cycle is defined as the interval between two adjacent moments of heel strike [1]. Another important event in the gait cycle is the moment when the toe leaves the ground. The duration it takes from heel strike moment to the toe-off moment is considered as the stance time and the rest is the swing time in one cycle. A simplified method was proposed according to the previous methods [20] [21] to identify the heel strike event from the joint trajectories. Since walking is an approximately periodic motion, the knee angle of heel strike moment is assumed to always start with a local minimum. All minima of the knee angle trajectory were examined and considered as potential heel strike moments. This method was verified by visual inspection as ground truth and got satisfying results.

2) Missing Value Interpolation:

Due to the variation of lighting conditions and walking speed, few angle values could be missing from the joint trajectory detection. These missing or inaccurate values were interpolated with smoothing spline interpolation method [22].

3) Joint Trajectory Normalization:

The length of trajectories varies from person to person because of the difference on walking speed. Therefore all trajectories were normalized to the same length. In our study, each spline joint trajectory was resampled using the spline function with the same sampling frequency of 100Hz and the generated 101 values represent the angle from 0% to 100% of the gait cycle accordingly.

D. Feature Extraction

Four types of features were stressed in this study: basic temporal features, time-domain kinematic features, frequency-domain kinematic features and symmetric features.

1) Temporal features:

Basic temporal parameters are composed of stride time, stance time, and stance ratio for both legs and double support time [1], i.e., the duration when both legs have contact with the ground. The stance ratio and double support time were computed using the equations

$$R_{stance} = T_{stance}/T_{stride} \quad (1)$$

$$T_{double} = \frac{1}{2}\left(\left(T_{stance2} - T_{swing1}\right) + \left(T_{stance1} - T_{swing2}\right)\right) \quad (2)$$

where the data of the leg with larger stride time are labeled with subscript "1".

2) Time-domain kinematic features:

Many studies have agreed that the most significant features of hip trajectory are the maximum value, minimum value, mean value and the range of motion (ROM); the most significant features of knee joint are the maximum value in stance, maximum value in swing, mean value and the ROM [23]. Accordingly, these values were obtained from the normalized trajectories as the time-domain kinematic features.

3) Frequency-domain kinematic features:

The frequency-domain feature descriptor of joint angles has been proposed in [24]. The joint angle data were considered as a complex series, $z(n) = KneeAngle(n) + j * HipAngle(n)$ where n is the sample number. The fast Fourier transform (FFT) pairs of $z(n)$ can be taken once the complex data is constructed with equations

$$Z(k) = \sum_{n=0}^{N-1} z(n) \exp\left(-j2\pi kn/N\right) \quad (3)$$

$$z(n) = \frac{1}{N}\sum_{k=0}^{N-1} Z(k) \exp\left(j2\pi kn/N\right) \quad (4)$$

where $N = 101$ and $k = 0,1,2,\ldots,N-1$. The magnitudes of the first six FFT coefficients were calculated using

$$X_k = \sqrt{R^2(k) + I^2(k)} \quad (5)$$

with $R(k)$ and $I(k)$ representing the real and imaginary parts of $Z(k)$ respectively. These features were labeled as $X_1, \ldots, X_5$ for one leg and $Y_0, \ldots, Y_5$ for another. The knee-hip angle plot of the average trajectories for three classes is depicted in Fig. 2. The curves are not closed, because the gait cycles obtained in the experiment are not ideally periodic.

4) Symmetric features:

Gait symmetry is a measure of the parallels between two lower limbs and controls the balance of walking. Referring to the recommendation from [25], the symmetry index was defined as

$$\mathrm{SY} = \max\left\{\mathrm{V_{left}}/\mathrm{V_{right}},\ \mathrm{V_{right}}/\mathrm{V_{left}}\right\} \quad (6)$$

TABLE II. List of All Features

Feature Type	Feature Index	Feature Name
Temporal	1, 2, 3	$T_{stride1}$ [a], $T_{stance1}$, $R_{stance1}$
	4, 5, 6	$T_{stride2}$, $T_{stance2}$, $R_{stance2}$
	7	T_{double}
Kinematic	8, 9, 10, 11	Max_{hip1} [b], Min_{hip1}, $Mean_{hip1}$, ROM_{hip1}
	12,13,14,15	Max_{hip2}, Min_{hip2}, $Mean_{hip2}$, ROM_{hip2}
	16, 17, 18,19	$Max_{stance1}$, Max_{swing1}, $Mean_{knee1}$, ROM_{knee1}
	20, 21, 22, 23	$Max_{stance2}$, Max_{swing2}, $Mean_{knee2}$, ROM_{knee2}
FFT	24,25,26, 27,28,29	X_0 [c], X_1, X_2, X_3, X_4, X_5
	30,31,32, 33,34,35	Y_0, Y_1, Y_2, Y_3, Y_4, Y_5
Symmetry	36,37,38, 39,40	SY_{stride}, SY_{stance}, SY_{swing}, SY_{hip}, SY_{knee}

a. Leg with larger stride time value is labeled with subscript "1"

b. Leg with larger ROM value is labeled with subscript "1"

c. Leg with larger first FFT value is labeled with "X"

where $\mathrm{V_{left}}$ and $\mathrm{V_{right}}$ represent the temporal and kinematic gait parameters of left and right limbs. The symmetry indexes of stride time, stance time, swing time, hip ROM and knee ROM were computed using equation (6) and declared as the symmetric features in this study. The indexes and abbreviations of all 40 features are listed in TABLE II.

E. Statistical Analysis

Study population characteristics were reported as mean values and standard deviation. Besides, each single feature was analyzed separately between every two of the three groups with one-way analysis of variance (ANOVA), which is a technique used for comparing means of two or more samples. The resulting p-value depicts the significant difference between two corresponding classes for a certain feature. For a particular feature, if the p-value between two groups satisfies $0.01<p<0.05$, this feature was regarded as a significant feature; if the p-value satisfies $p<0.01$, it was taken as a very significant feature. Both significant and very significant features were marked as selected features in the classification stage.

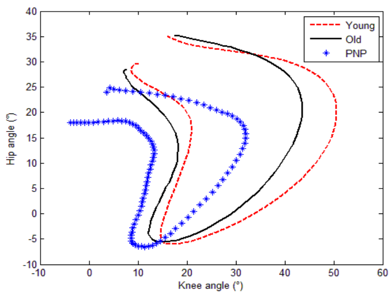

Fig. 2. The knee-hip angle plot of average trajectories for three groups.

F. Classification Using ANN

1) Network structure:

The problem being handled in this study is to classify the young healthy, old healthy and PNP patients depending on the generated 40 gait features. A two-layer-feed-forward neural network, with 15 sigmoidal neurons in hidden layer and 3 sigmoidal neurons in output layer was created. The training algorithm implemented in the network is Levenberg-Marquardt (LM) based backpropagation (BP). Since it has been emphasized that the optimal size of hidden layer is usually between the size of input and output layer [26], the number of neurons in hidden layer was set to 10.

2) Accuracy evaluation:

The most commonly used method to evaluate the accuracy of a classifier is cross-validation. Due to the size limitation of the study, a two-fold cross validation was applied; i.e. the dataset is randomly partitioned into two subsets of equal size. One set is used for training and another for testing, then two sets were switched and network is retested. The average accuracy of both trials is computed as the overall accuracy. In order to improve the generalization of the network, the mentioned training and validation steps were repeated for 300 times and the final accuracy is the average of all repetitions [27]. A typical measure of classification accuracy is defined as

$$Acc = (TP + TN)/(TP + TN + FN + FP) \qquad (7)$$

where *TP*, *TN*, *FP*, and *FN* represent true positive, true negative, false positive, and false negative instance numbers.

3) Feature partitioning and grouping

In order to find the most significant feature type and the most significant features in each type, 40 features were grouped and tested in the following order: 1) Use each single type of features; 2) Use every two types of features; 3) Use every three types of features; 4) Use all 40 features; 5) Use all selected very significant features; 6) Use all selected significant and very significant features.

III. RESULTS AND DISCUSSION

This session will elaborate the attained statistical results for each gait feature and the classification outcome from ANN.

A. Statistical Analysis on each Feature

Summarized results of the statistical analysis are presented in TABLE III. It can be seen from the mean values and *p*-values of each feature, and the knee-hip plot in Fig. 2 that:

- For temporal features, PNP patients show significant decrease on stride time and increase on stance time compared with both old and young healthy subjects while old healthy subjects show insignificant increase on stance time compared with young subjects. Therefore double support time is significantly increased on PNP patients and slightly increased on old healthy.
- As regards the kinematic time-domain features, the hip ROM of old healthy subjects indicated a very significant decline compared with the young subjects while decreases were found in the PNP group compared with the group of old and young subjects on most of the features. The decrease of joint ROM on PNP can be observed from the curves in Fig. 2 as well.
- FFT coefficients of the joint trajectories for each group have also some obvious differences, especially the first three coefficients.
- In general, the symmetry of the old group is slightly worse than of the young group, and the PNP patients have the worst symmetry. However, no significant difference was observed from the results.
- The most significant features to distinguish between the old and the young groups are: $R_{stance1}$, $MAX_{stance1}$, $MEAN_{knee1}$, ROM_{knee2} and X_3. The most distinguishing features for the old and the PNP group are: $T_{stride1}$,$T_{stance2}$, MAX_{hip1}, MAX_{hip2}, $MEAN_{hip2}$, ROM_{hip2}, MAX_{swing1}, $MAX_{stance2}$, $MEAN_{knee2}$, X_0, Y_0, and Y_1.

To sum up, 12 significant features, including 6 temporal, 2 kinematic, 3 FFT, and 1 symmetric features, together with 15 very significant features, including 0 temporal, 10 kinematic, 5 FFT, 0 symmetric features, were observed and selected from the overall statistical results. All conclusions above are concordant with the previous findings mentioned in Section I.

B. Classification Performance with ANN

1) Classification based on individual and combined feature sets:

Performance results using ANN are depicted in Fig. 3. As can be seen from Fig. 3(a) that the maximum accuracies achieved were 94.2%, 94.8% and 94.8% for young, old and PNP groups respectively with single kinematic feature set. The FFT feature set reached the second highest accuracies for all three classes while the symmetric feature set gave the lowest accuracies. When using combined features of 2 sets, as illustrated in Fig. 3 (b), the average performance was improved compared with using only one feature set with the highest accuracies of 95.9%, 96.7%, and 96.6%. As three sets were used, it can be seen from Fig. 2 (c) that the general outcome did not show overwhelming improvement; only the accuracy of classifying PNP group reached 0.1% higher than in Fig. 2 (b). This indicates the existence of redundant information while introducing additional features. In summary, the kinematic features give the best results for classification of all three groups, while the FFT, temporal and symmetric features achieved the second best, third best and worst performance; combing two feature sets can improve the performance considerably; no significant improvement was observed when more feature sets were introduced.

2) Classification based on selected features:

Twelve significant features and 15 very significant features were selected from the ANOVA results and the same validation procedures were conducted. The results depicted in Fig. 3(d) demonstrate that: 1) results obtained by using all features were close to the results of using three feature sets; 2) comparative outcomes were achieved by using only 15 very significant features relative to using all features; 3) the combination of all significant and very significant features reached the highest accuracies, i.e. 96.2%, 97.0% and 96.9%, among all tests carried out. It can be concluded that the usage of all features is not able to enhance the effectiveness of the classification; ANOVA is a possible technique for feature selection; selected features can give an optimal performance.

IV. CONCLUSION

Neuropathic gait is a common pathological gait pattern among the elderly, while changes on gait brought by healthy aging can be observable as well. Many statistical studies have been conducted on gait parameters of healthy old and PNP patients. However, it has not been well established that which features provide the best representation of the characteristics of those groups. Moreover, seldom studies utilize machine learning algorithms, which are becoming a powerful tool for clinical gait analysis, to discriminate those types of gait.

In this study, a robust markerless gait detection system was employed and free walking experiments in normal clinical environment were performed on 10 young healthy subjects, 10 old healthy subjects and 10 PNP patients. Raw data preprocessing and gait feature extraction procedures were described in detail. Statistical analysis utilizing one-way ANOVA and classification with a two-layer-feed-forward ANN were conducted, the results indicate that: 1) 1 temporal and 3 kinematic parameters of healthy old people show significant decreases compared with healthy young group; 2) 2 temporal and 7 kinematic features indicate significant decrease relative to the healthy old subjects; 3) declination of symmetric evaluation was observed in both old and PNP groups without significant changes; 4) among all 4 types of features, kinematic feature set gives the best classification performance for all classes; 5) features selected from ANOVA outperform the rest of feature combinations among all tests and one way ANOVA can be used as a potential feature selection method.

This is the first study applying ANN on several types of gait features for both healthy subjects and PNP patients to the best of our knowledge. It may provide in future a useful tool that can discriminate between early PNP and healthy gait patterns from various features for the clinicians. Future perspectives of our work are to develop reliable methods for early stage diagnosis and medication effort determination for PNP patients. Also we will compare the performance of different machine learning methods and propose additional ways of feature extraction.

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TABLE III. STATISTICAL ANALYSIS ON EACH GAIT FEATURE

Feature Type	Feature Name	Young		Old		PNP		*p*-value		
		Mean	SD	Mean	SD	Mean	SD	Young&old	Old&PNP	Young&PNP
Temporal	$T_{stride1}$ (second)	**1.297**	0.074	**1.277**	0.127	**1.430**	0.160	**0.672**	**0.029 ***	**0.028 ***
	$T_{stance1}$ (second)	**0.837**	0.060	**0.850**	0.100	**0.967**	0.147	**0.721**	**0.053**	**0.019 ***
	$R_{stance1}$	**0.645**	0.019	**0.665**	0.018	**0.674**	0.046	**0.027 ***	**0.555**	**0.080**
	$T_{stride2}$ (second)	**1.207**	0.058	**1.203**	0.107	**1.337**	0.173	**0.932**	**0.053**	**0.037 ***
	$T_{stance2}$ (second)	**0.787**	0.042	**0.800**	0.080	**0.900**	0.121	**0.647**	**0.043 ***	**0.012 ***
	$R_{stance2}$	**0.652**	0.016	**0.665**	0.026	**0.674**	0.033	**0.207**	**0.515**	**0.077**
	T_{double} (second)	**0.372**	0.047	**0.397**	0.058	**0.483**	0.128	**0.305**	**0.066**	**0.018 ***
Kinematic	MAX_{hip1} (degree)	**40.406**	7.983	**36.146**	7.333	**29.452**	6.294	**0.230**	**0.042 ***	**0.003 ****
	MIN_{hip1} (degree)	**-6.658**	6.411	**-12.233**	9.214	**-12.410**	6.296	**0.134**	**0.961**	**0.058**
	$MEAN_{hip1}$ (degree)	**17.682**	7.539	**11.958**	5.296	**9.596**	4.554	**0.065**	**0.299**	**0.009 ****
	ROM_{hip1} (degree)	**47.064**	4.638	**48.379**	11.421	**41.862**	11.063	**0.740**	**0.211**	**0.187**
	MAX_{hip2} (degree)	**33.174**	6.890	**35.676**	6.576	**25.138**	5.954	**0.417**	**0.001****	**0.012 ***
	MIN_{hip2} (degree)	**-6.656**	7.069	**-1.583**	7.465	**-3.924**	6.411	**0.136**	**0.462**	**0.377**
	$MEAN_{hip2}$ (degree)	**14.204**	7.288	**17.892**	6.564	**11.901**	5.424	**0.250**	**0.039 ***	**0.433**
	ROM_{hip2} (degree)	**39.830**	6.645	**37.259**	6.870	**29.062**	4.856	**0.406**	**0.006 ****	**0.001 ****
	$MAX_{stance1}$ (degree)	**23.278**	6.056	**13.599**	5.909	**15.650**	5.714	**0.002 ****	**0.440**	**0.010 ****
	MAX_{swing1} (degree)	**57.560**	10.069	**50.927**	12.670	**37.690**	10.559	**0.211**	**0.021 ***	**0.001 ****
	$MEAN_{knee1}$ (degree)	**26.747**	7.348	**20.066**	6.619	**15.531**	7.518	**0.047 ***	**0.169**	**0.003 ****
	ROM_{knee1} (degree)	**51.352**	8.623	**50.713**	11.500	**41.828**	11.651	**0.890**	**0.103**	**0.052**
	$MAX_{stance2}$ (degree)	**20.585**	9.058	**25.393**	12.228	**14.007**	6.084	**0.331**	**0.017 ***	**0.073**
	MAX_{swing2} (degree)	**46.567**	7.349	**42.915**	13.590	**32.691**	10.225	**0.464**	**0.073**	**0.003 ****
	$MEAN_{knee2}$ (degree)	**22.647**	6.916	**23.372**	11.063	**12.985**	6.066	**0.862**	**0.018 ***	**0.004 ****
	ROM_{knee2} (degree)	**41.778**	3.169	**36.337**	4.152	**34.405**	9.887	**0.004 ****	**0.576**	**0.038 ***
FFT	X_0	**3406.536**	883.932	**3124.058**	1062.530	**2138.702**	757.285	**0.526**	**0.028 ***	**0.003 ****
	X_1	**1781.771**	378.710	**1540.229**	512.409	**1235.673**	510.245	**0.246**	**0.200**	**0.014 ***
	X_2	**702.047**	134.123	**514.448**	127.309	**610.121**	288.433	**0.005 ****	**0.350**	**0.373**
	X_3	**89.469**	56.973	**84.947**	59.467	**154.213**	95.692	**0.864**	**0.068**	**0.083**
	X_4	**46.763**	28.563	**77.986**	48.387	**128.034**	70.020	**0.096**	**0.079**	**0.003 ****
	X_5	**62.367**	37.185	**57.627**	44.879	**78.860**	41.883	**0.800**	**0.288**	**0.364**
	Y_0	**2594.968**	869.111	**2274.753**	838.437	**1554.180**	656.743	**0.413**	**0.046 ***	**0.007 ****
	Y_1	**1698.932**	232.907	**1784.670**	553.482	**1243.297**	418.053	**0.657**	**0.024 ***	**0.008 ****
	Y_2	**633.584**	158.354	**758.426**	207.918	**665.100**	213.694	**0.148**	**0.335**	**0.712**
	Y_3	**115.266**	65.703	**124.831**	63.263	**205.254**	117.788	**0.744**	**0.073**	**0.049 ***
	Y_4	**55.821**	38.846	**88.211**	58.765	**110.325**	55.253	**0.163**	**0.397**	**0.020 ***
	Y_5	**53.128**	37.241	**66.173**	43.236	**67.509**	43.233	**0.479**	**0.946**	**0.436**
Symmetry	SY_{stride}	**1.075**	0.049	**1.061**	0.043	**1.074**	0.063	**0.493**	**0.594**	**0.955**
	SY_{stance}	**1.064**	0.053	**1.080**	0.052	**1.073**	0.057	**0.491**	**0.784**	**0.699**
	SY_{swing}	**1.097**	0.064	**1.095**	0.077	**1.078**	0.185	**0.938**	**0.802**	**0.767**
	SY_{hip}	**1.195**	0.105	**1.323**	0.323	**1.433**	0.279	**0.250**	**0.422**	**0.021 ***
	SY_{knee}	**1.226**	0.163	**1.395**	0.277	**1.235**	0.244	**0.114**	**0.186**	**0.930**

*significant features   **very significant features

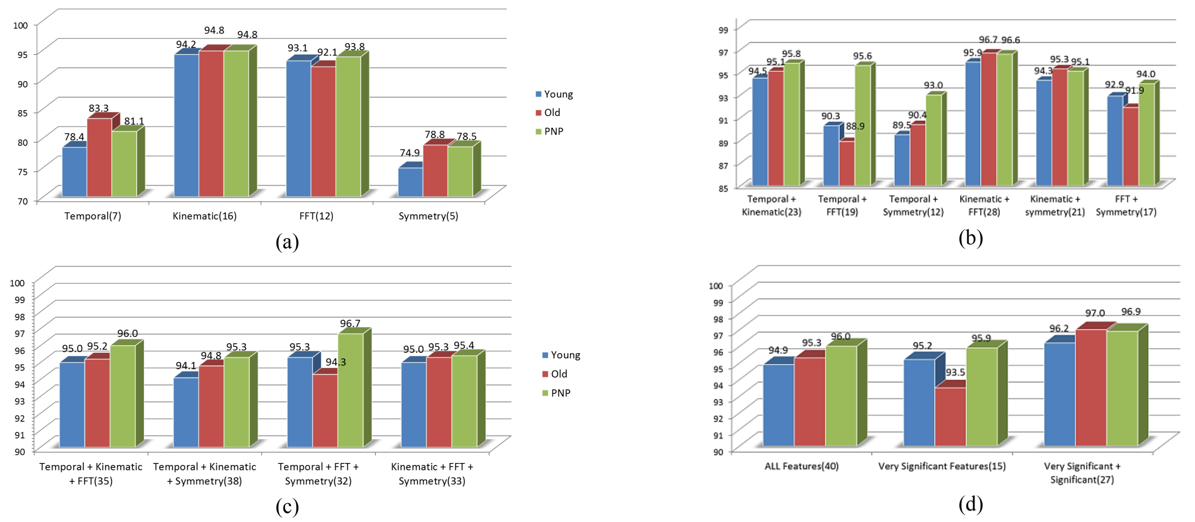

Fig. 3. Classification accuracies of all three classes (in %) using ANN and combination of features. The numbers in parentheses are the number of features.