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Diagnosis of the motion pathologies based on a reduced kinematical data of a gait

Abstract. *The paper presents method of motion analysis supporting diagnosis of gait abnormalities on the basis of reduced kinematical data of a gait. The proposed method consist of the following steps: kinematical data reduction by Principal Component Analysis, determination of the Fourier component for the 3D PCA trajectories and supervised learning. To examine proposed approach, we have collected database of gaits containing data of coxarthrosis patients. We have got 100% of classification accuracy for the considered disease.*

Streszczenie*. W artykule zaprezentowano metodę analizy danych ruchu dla celów wspierania diagnostyki nieprawidłowości chodu. W kolejnych krokach przeprowadzana jest redukcja wymiarowości kinematycznych danych chodu z wykorzystaniem metody analizy składowych głównych, wyznaczane są składowe Fouriera dla otrzymanych trójwymiarowych trajektorii PCA oraz przeprowadzane jest uczenie nadzorowane. W celu weryfikacji zaproponowanej metody zgromadzono bazę danych przejść ze schorzeniami stawu biodrowego, dla której to udało się uzyskać 100% skuteczność klasyfikacji.. (****Diagnostyka patologii ruchu na podstawie zredukowanych danych kinematycznych****).*

Keywords: motion capture, coxarthrosis, supervised learning, Fourier transform
Słowa kluczowe: pomiar ruchu, koksartroza, uczenie nadzorowane, transformata Fouriera

Multimodal motion capture

In the opinion of the medical experts, skilled orthopedist is able to evaluate and recognize abnormalities of a gait based only on a visual gait observation. This means gait contains essential data for the proper medical diagnosis. The crucial is process of their exploration and extraction from a high dimensional motion data. The manual gait analysis by medical expert has important disadvantages. The method is subjective, expensive and there is no possibility to determine numerical measures of the diagnosed pathologies.

Still developing techniques of a motion capture give new opportunities of the multimodal acquisition of motion. Example of high tech motion capture laboratory is human motion laboratory of Polish-Japanese Institute of Information Technology [1]. It can acquire motion data through simultaneous and synchronous measurement and recording of motion kinematics, muscle potentials by electromyography, ground reaction forces and video streams in high definition format, HML supporting system allows for storing, playing and browsing data, The data of above mention subsystems are wide, accurate and allow for a deep analysis of motion. However, shortcomings of such an ability to capture multimodal motion data are costs of the equipment and poor mobility of the laboratory. Currently, there are possibilities to capture motion kinetics with noticeable worse precision, but by much less expensive systems. They are based on the Z-buffer estimation, which can be transformed to cloud point representation and later to skeleton data in for instance Acclaim format. However, it is necessary to explore and extract motion data for a given medical diagnosis prior the deployment of the proposed method. The choice of the accurate and complete motion capture for this task is surly reasonable.

Coxarthrosis

Coxarthrosis is a degenerative disease of hip joint with multifactor etiology and resulting in disturbances of gait [2]. Coxarthrosis is based on premature wear and degeneration of tissues comprising the hip joint, articular cartilage, subcartilaginous bone stratum, articular fluid, articular capsule, ligaments and muscles. The course of the illness causes damage to the cartilage, restructuring of the bones with formation of exostosis, osteosclerosis of the subcartilaginous stratum and formation of cysts. Often the function of the synovial membrane - the internal layer of the articular capsule is disturbed. The degenerative hip joint illness is accompanied by pain which comes from the joint while in motion; it also causes changes revealed by X-ray examination. The degenerative hip joint illness is revealed as early as in the second or third decade of life, and occurs in 60% of the population over 60 years of age; it is the most frequent cause of joint pain. The progress of the illness is determined by numerous predisposing factors, such as old age, ethnic factors, congenital factors, inappropriate biomechanics of the joint, obesity, walk of life, physical activity, large bone mass and hormone levels. So far no single reason for the illness has been discovered. The degenerative hip joint illness is a result of many factors which affect both the joint itself and the whole organism. If the etiological factor is undetected, we deal with primary or idiopathic degenerative illness (*arthrosis deformans idiopathica s. primaria*). In the etiology of this form, an import ant role is played by local inadequacies of circulation within joints, which lead to changes in the joint liquid that feeds the cartilage. The illness may also be affected by heavy load on the joints, generated by doing professional sports activities or hard physical work. A larger group within degenerative joint illness is the secondary degenerative a result of certain congenital or hereditary factors, such as: congenital hip dysplasia, haemophilia, haemochromatosis, alkaptonuria. Acquired factors: local, e.g., injuries, joint sprains, a single serious injury or microinjuries, bone fractures with anomalous synostosis, septic or tuberculous inflammation of the joint, aseptic bone necrosis. Systemic: metabolic diseases, such as uric gout, rheumatic inflammation of the joints, chronic corticotherapy and neurological disturbances [3].

Existing diagnostic techniques based on motion capture data

Several publications can be found in the literature, devoted to using the gait indexes in studying characteristic features of gait in cohorts of patients defined by their clinical status. In these publications measurements of gait indexes are further combined with several machine learning techniques in order to extract appropriate information. Some of the publications and methodologies are overviewed below. In the paper [4] four types of health problems of the elderly are detected: Parkinson's disease, hemiplegia, pain in the leg and pain in the back. The proposed method is based on the feature extraction approach and supervised learning. The 13 different features, calculated directly from the motion capture sequences, are prepared by the medical expert. For instance, one of them represents the quotient between maximal angle of the left knee and maximal angle of the right knee. Obtained feature's vectors are classified by the decision tree and neural network classifiers. In the initial condition, without noise and all tags included, 100% accuracy has been achieved. Adding noise and removing the tags cause only insignificant decrease of the accuracy to 99%.

A method of the gait asymmetry assessment, applicable to many motion disorders, is proposed in [5]. It is extension of the well known symmetry index, but does not require the normalization to the crucial reference value. Different application of the motion capture to the PD diagnosis is proposed in [6]. The task is even more challenging, because the authors try to separate the patients with symptoms similar to PD, but without evidence of dopaminergic deficits. Once again three types of gaits are defined: normal walk, line walk and tandem (heel-toe) walk. On the basis of the acquired data 15 features are calculated and statistical analysis is performed to assess the difference between tested groups of patients. In [7] the gait with turning is analyzed for the PD diagnosis.

A feature extraction approach based on the wavelet transform for the distinction between normal and pathological gait is presented in [8]. To discover gait signatures of the collected dataset the clustering by self organizing maps is used. The analyzed gait disturbances are as follows: polio, spina-bifida and cerebral palsy including symmetrical diplegias, left and right asymmetrical diplegias and left and right hemiplegias. The results are visualized and seem to confirm the discrimination ability of the proposed method. The application of the motion capture to compare the gait functions of the patients submitted to total hip arthroplasty through lateral and posterolateral approaches is presented in [9].

Collected database

. We have used PJWSTK laboratory with Vicon motion capture system [1] to acquire human gaits. We have collected database of 90 gaits coming from 15 different patients – 7 of them with diagnosed coxarthrosis on the basis of an earlier different examinations and 8 of them without coxarthrosis. We have specified the gait route, the straight line of the 5 meters long. The acquiring process started and ended with T-letter pose type because of the requirement of the Vicon calibration process. Example collected gaits of the patients with and without coxarthrosis are presented in Figure 1.

On the basis of the markers location the skeleton model containing 22 joints and 23 segments is estimated. The motion data is stored in ASF.AMC format as sequence of following poses. Each pose is described by 69 Euler angles – 66 represent joints rotations and remaining three global skeleton rotation. Additional three values are necessary for a global translation.

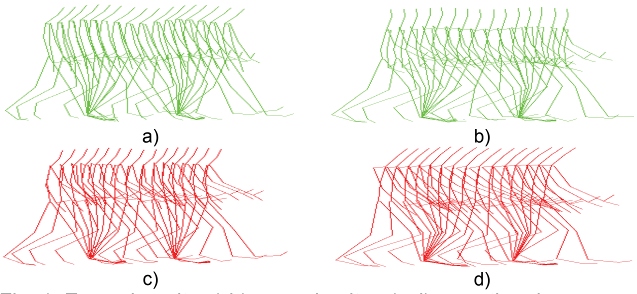

Fig. 1. Example gaits a),b) normal gaits, c), d) coxarthrosis

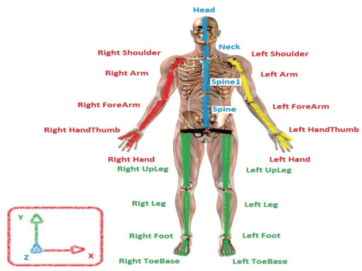

Fig. 2 Skeleton model

Dimensionality reduction of a motion data

There is lots of research made on the dimensionality reduction of the motion data. The classical approaches do the work on the level of the pose descriptors. Examples of using linear methods can be found in [10][11][[12] and non-linear in [13][14].

Recently the multilinear reduction methods for tensor objects are gaining more attention. They allow to reduce multi-dimensional objects indexed by multiple indices. The motion sequences are addressed by the frame number and pose parameter index, that means whole sequences can be reduced, not only the pose descriptions The multilinear PCA method for gait recognition is presented in [15] and multilinear ICA for face recognitions in [16]. The multilinear methods has one important disadvantage - they require the same dimension sizes of reduced objects - motion frames and pose descriptors. It means all motions have to be time scaled to the same number of frames - the comparison should be performed only for the corresponding gait cycles and the analysis does not take into consideration speed of the gait.

Principal component analysis

There is the thesis of the nonlinearity of pose spaces which promotes nonlinear reduction techniques [17]. However, it is not strictly proved and our earlier research done on the pose identification [18] has not confirmed the advantage of the non linear Kernel PCA in the classification. That is why we have started with standard Principal Component Analysis.

The PCA method calculates linear independent combinations Y of the inputs attributes X with the greatest variances. In fact it determines new base V^T of the vector space. It turns out, that the base created by the eigenvectors of the covariance attributes matrix satisfies the demands.

$$(1)\quad y = \begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_{n-1} \end{bmatrix} = V^T \cdot x = \begin{bmatrix} v_0^T \\ v_1^T \\ \vdots \\ v_{n-1}^T \end{bmatrix} \cdot \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{n-1} \end{bmatrix}.$$

The variances of the new attributes are determined by corresponding eigen values. Thus, we can sort the new attributes according to their variances and remove the less informative ones with the smallest variances.

There is always possibility to return back to the original space by the inverse transformation $\left(V^T\right)^{-1}$.

To reduce the original space some subset of the first few PCA components is chosen, which covers most of the input variance, for instance 90% or 95%. Going back to original space without removed values can cause remarkable errors in spite of very low variance been missed. That is the reason for the normalization of the input attributes by shifting mean value to zero and applying reverse shifting after inverse transform. In some cases if the attributes have different ranges and different meaning they are linearly transformed to the identical standard deviation. In case of pose attributes represented by the angles in the radians scale, it is not necessary.

The way of covariance matrix estimation is very important aspect of PCA. It is usually based on the classifier trainset. However, it is possible to use only poses from the given reduced motion for the motion data. The second case seems to produce incomparable data of different motions, but ultimately identification accuracy will be decisive.

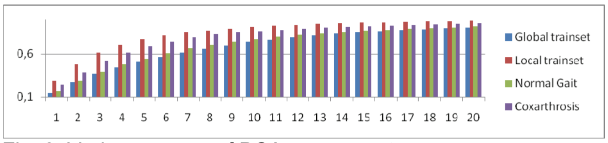

Fig. 3. Variance cover of PCA components

Figure 3 presents variance cover of the first n PCA components for the global trainset coming from all collected gaits, local train dataset built only from the poses of the reduced motion, from poses of the normal gaits and gaits of patients with diagnosed coxarthrosis. .As it was expected the global train dataset gives much lower covers - it has greater variance, which requires more components to store similar percentage of the information. Slightly better covers have coxarthrosis gaits in comparing to normal gaits, which means that their joints movements have lower variations or they are more correlated.

Table 1. Linear factors of the first PCA component

Global trainset		Normal gaits		Coxarthrosis	
Left Shoulder	0,1089	Neck	0,0883	Left Foot	0,0829
Left Arm	0,1031	Right Arm	0,0820	Right Hand	0,0825
Left Hand	0,0963	Left Shoulder	0,0817	RightShoulder	0,0759
RightShoulder	0,0894	Spine	0,0789	Left Shoulder	0,0736
Right Hand	0,0756	Left Arm	0,0768	Right Foot	0,0699
Left Foot	0,0585	RightShoulder	0,0722	Left Arm	0,0680
Neck	0,0526	Right UpLeg	0,0604	Spine	0,0629
Right Arm	0,0522	Left Hand	0,0574	Spine1	0,0580
Left UpLeg	0,0492	Head	0,0556	Left Hand	0,0549
Right Foot	0,0485	root	0,0511	Neck	0,0505
Spine	0,0484	Left UpLeg	0,0475	Left UpLeg	0,0459

Table 1 contains aggregated linear factors of the first PCA component for the three different trainsets. The aggregation is computed as the sum of the absolute values of the three Euler angles representing rotation of the given joint, thus it presents total dependency between the component and the joint. First PCA component is the one with greatest variance, which means it should promote the uncorrelated joints with wide ranges and great variations of their movements. The man difference between normal and coxarthrosis gaits are much greater influences of the feet and hands movements on the first PCA for the coxarthrosis gaits. It can be caused by a balance problems of the disease.

In Figure 4 we have visualized gaits restored by a given number of the first PCA components. We have only reduced the skeleton rotation parameters leaving the translation values in the original form. For the single PCA component, beside starting and ending T pose, the body movements are almost invisible. It much better for the 5 and quite well for 20 components.

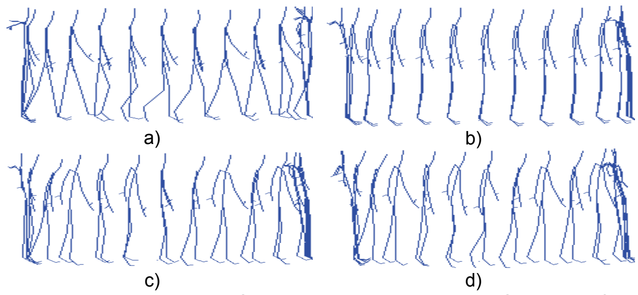

Fig. 4. Reduced gait by PCA a) original gait, b) one PCA gait c) five PCA gait, d) twenty PCA gait

PCA motion trajectories

In Figure 5 the motion of trajectories containing first three PCA components, of the four example non-coxarthrosis and coxarthrosis gaits labeled with green and red colors respectively are presented. There are visible gait loops which correspond to following steps. They have much more regular shapes for the local trainset which is matched better to the reduced motion.

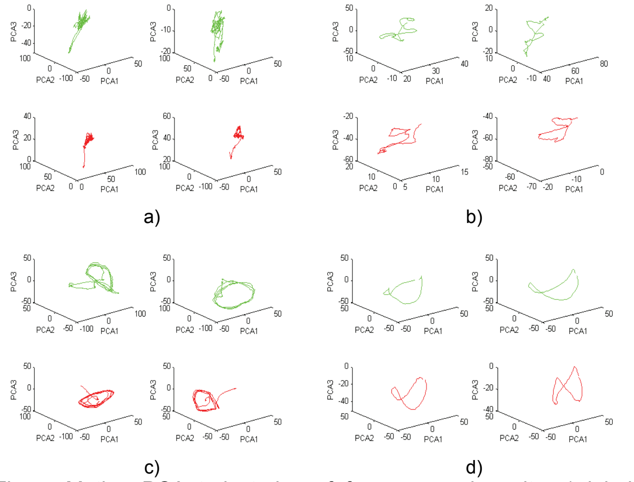

Fig. 5 Motion PCA trajectories of four ex ample gaits a)global trainset and full gait, b)global trainset and main cycle, c) local trainset and full gait, d) local trainset and main cycle

There are some difference between coxarthrosis and non-coxarthrosis gait trajectories, but in fact it is very difficult to state simple discrimination rules between those two classes. However we excepted the discrimination is possible and that has why decided to apply one more transformation of the trajectories. We calculated Fourier components. For every sequence of the following coordinates the classical Discrete Fourier Transform is performed:

(2) $$a_i = \frac{1}{L-1}\cdot\sum_{j=1}^{L} x_i \cdot e^{-i\cdot\frac{2\pi}{L-1}\cdot i\cdot j} \quad b_i = \frac{1}{L-1}\cdot\sum_{j=1}^{L} y_i \cdot e^{-i\cdot\frac{2\pi}{L-1}\cdot i\cdot j}$$

$$c_i = \frac{1}{L-1}\cdot\sum_{j=1}^{L} z_i \cdot e^{-i\cdot\frac{2\pi}{L-1}\cdot i\cdot j}$$

To achieve rotation invariance of the coefficients the total length of the absolute values of the complex numbers for every components is calculated and to obtain magnification invariance the normalization is applied at the end:

$$(3)\qquad r_i = \sqrt{(a_i)^2 + (b_i)^2 + (c_i)^2} \qquad w_i = \frac{r_i}{r_1}$$

The normalized Fourier coefficient for the gaits from Figure 5 are presented in Figure 6. It seems that discrimination of the coxarthrosis gaits is easily to be noticed. There is much greater impact of the high frequencies especially in comparing to low frequencies for the coxarthrosis trajectories. It best seen for the global trainset and full gait, but it is still visible for the global trainset and main cycle or even local trainsets cases. The greater values of the high frequencies can be caused by the slight, non cyclic movements during the gait.

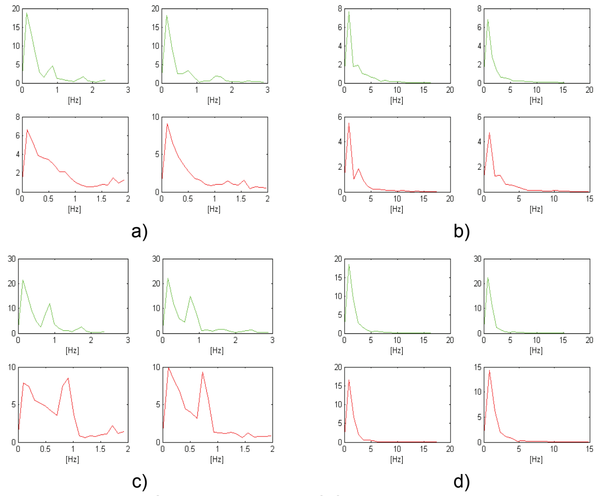

Fig. 6. Motion PCA trajectories of four example gaits a) global trainset and full gait, b)global trainset and main cycle, c) local trainset and full gait, d) local trainset and main cycle

There are similar observations for the other gaits collected in the database, However to confirm the hypothesis of possible discrimination of the coxarthrosis gaits on the basis of normalized Fourier coefficients of PCA motion trajectories we performed classification experiment by supervised learning techniques. We chose two statistical classifier: Naïve Bayes with normal distribution and distribution estimated by the kernel based method and nearest neighbors classifier. To split dataset into train and test parts we applied cross validation. We have obtained 100% of classification accuracy, which means that in our collected database the discrimination is possible. Because of the limited database size, stating the general conclusion is premature, but obtained results surely does not deny the thesis of diagnosis of coxarthrosis disease on the basis of reduced kinematic data of a gait.

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