USAGE OF PCA FOR PARAMETERIZATION IN VERTEBRAL COLUMN DYNAMIC EXAMINATIONS

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Abstract
The main purpose of this thesis it to describe a method for a parametric analysis of human walk. Measurement data were taken with stereovision methods. To obtain the data, position of markers located on human body was registered. Parameterization was achieved through eigenvector and covariance matrix of position, speed and acceleration trajectory calculation for every of those markers. Prepared software allows signal filtration, trajectory visualization and necessary calculation performance. Fourier models of patients' movement were also used in the research. Evaluations, preprocessing and reconstructions 3D were executed on numerous students of the University of Valencia and results were elaborated at Warsaw University of Technology.

Key words: *stereovision, vertebral column, dynamic, eigenvalues, eigenvectors*

Introduction

Human walk observation can be a very valuable source of information for many specialists from areas like medicine, psychology or sports. People with short-sightedness, even without glasses, can recognize a well known person from a big distance just recognizing his/her specific walk manner. Human beings use a similar orthograde bipedal mode of locomotion.

Minor individual differences however allow distinguish people by the way they walk. A well known fact is the difference between male and female gait. A person suffering pain shows another, heavier, gait than a healthy person, without pain. Gait abnormalities can be observed at people with persistent spine pathologies as scoliosis, lordosis and kyphosis. Software created in Ruhr University in Bochum and Queen's University in Kingston allows the animation of human walk according to sex, weight, mood etc.

These observations are direct but non-invasive and can be compared with subjective observations which were remembered one time so can be treated just in qualitative sense. The problem is to objectify these observations through mathematical models or parameterization approaches to describe human walk manner. The aim of these descriptions is the automatic classification of human gait.

Problem and goal

The main goal is to describe human spine movement meanwhile a normal and calm gait of the observed patients. The description should be preceded in a parametric way, so the results can be used for automatic classification methods. Methods like artificial neural networks or support vector machines can distinguish a normal healthy behaviour from abnormalities indicating health disorders, to achieve that the description should be multidimensional vector or coefficients matrix. This work is based on real data gathered with non-invasive methods, using infrared light and stereovision methods. The data has been gathered in a special constructed laboratory of image analysis, from over 100 voluntary students from Physics, Pharmacy and Mathematics departments of the University of Valencia. Regardless to the laboratory dynamic measures on treadmill, every volunteer was examined by a MD orthopaedist (Gonzales et al., 2006). The evaluation consisted of a complete case history including information regarding volunteer's general condition and health, a family history, presence of absence of back pain, etc. A complete physical examination was also performed focusing on spine alignment and range of motion. Another goal of this thesis is also the preparation for a future new non-invasive and economic method for screening and early diagnosis of pathological changes in growth phase. Method can also be used in pain cure clinics for therapy advancement.

Methods

A laboratory provided with 3D system was designed for the recording of the movement of volunteer's spine, head, legs and arms while human walks on a treadmill. We have chosen specific points of the human anatomy in order to apply on the skin special markers made from reflecting materials.

Four video cameras located symmetrically had been used. 2 cameras were located on the left and 2 on the right side and accordingly one on the top and one on the bottom for each side. Lay out of the cameras allows at least two cameras to record all the disposed markers at every moment.

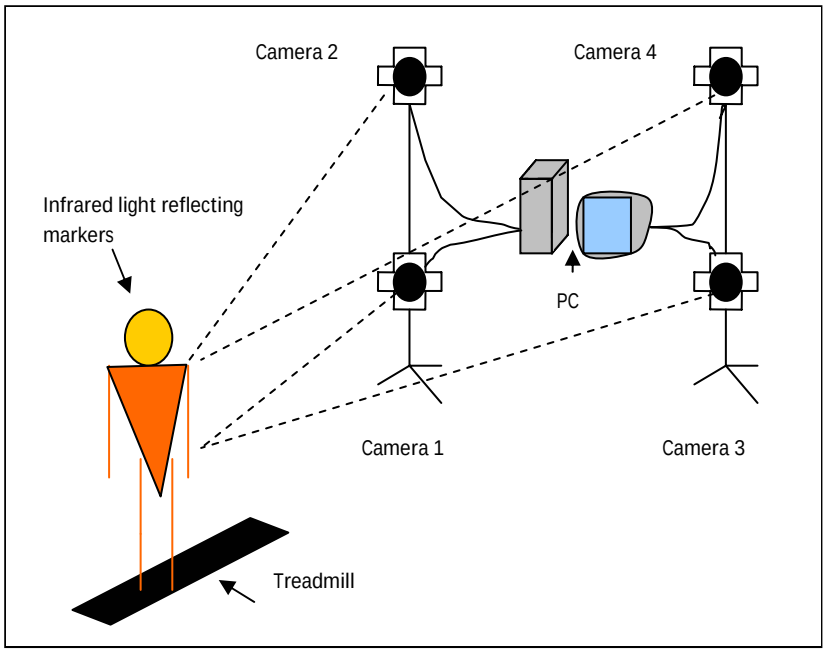
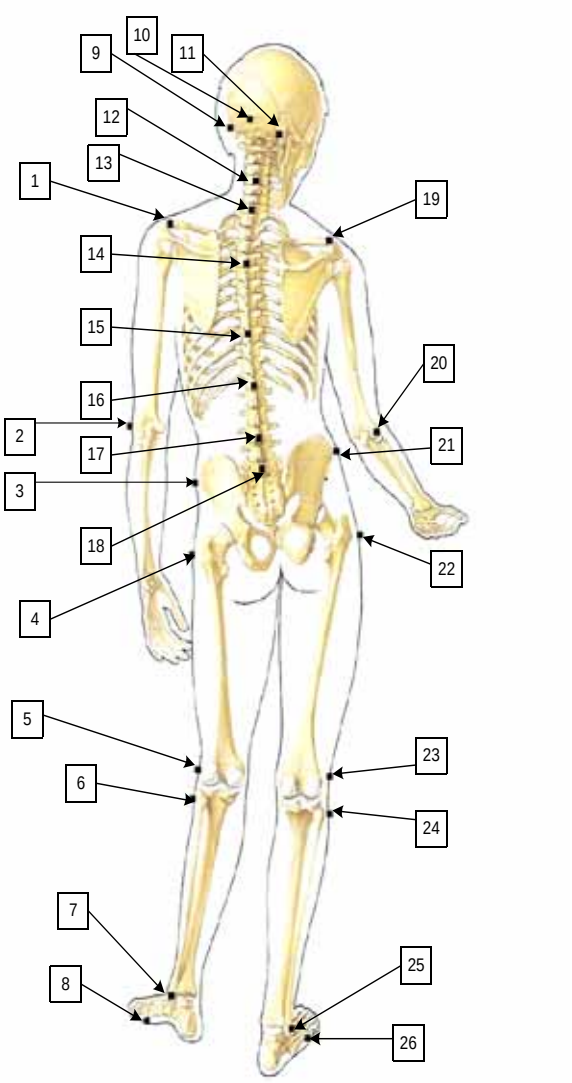


Figure 1. Data collection method.

The laboratory consists of: 4 Sony XC55 cameras, with infrared filters, blocking all other light spectrums which are used to „catch" images; 4 LED sets that emit infrared light. Infrared reflecting markers on patient body to trace his/her movement. Framegrabber – (device controlling cameras work). PC with specialized software to record digitally image from the cameras. Treadmill, that allows a patient to stay in the same place relatively to the cameras. In every moment the patient is visible by the cameras.

The cameras are calibrated due to treadmill, what means that in every moment all coordinates for each marker on a human body can be determined. All those elements form image and data collection system with their visualization and reconstruction. On patient's body are located 26 markers (7 on chosen vertebras, 3 on skull's occipital plane, each 2 on elbows and arms, 2 on hips and 10 on legs). Markers location is illustrated on the Figure no. 2. Patient walks on the treadmill's belt with a comfortable velocity for him/her. Two sessions are held, each one for 30 seconds, what gives 450 images for each camera.

As a result we achieve 4 sets of 2 dimensional images (one per camera). For every marker its optical gravity centre is calculated and later for a chosen pair of the cameras 3D reconstruction of all 26 points is performed. Epipolar geometry is used for the calculations (Grabowski, 2005). Output of the reconstructions has a form of a matrix with dimensions 450x79, where in respectively columns are coordinates (x, y, z) for each marker (26x3=78) and in the last column (79) there is the time gap between consecutive exposures (App. 65ms). Number of rows corresponds with number of recorded images in the session. Data obtained from record session should be previously pre-processed. Artefacts corresponding with accidental light flashes from objects in the laboratory should be removed. For that purpose are used average window filters and interpolation methods. Other kind of distortion is irregular human gait. It appears as a tendency to walk faster and slower in some moments and changing position on the treadmill's belt from left to right and backwards. A way to eliminate those noises is to move point of reference to so called pseudo gravity centre.



Number	Markers location
1	acromion
2	epicondylus lateralis humeri
3	spina iliaca anterior superior
4	trochanter major
5	condylus lateralis femori
6	caput fibulae
7	malleolus lateralis
8	tuberositas ossis metatarsalis V
9	processes mastoideus
10	inion
11	processes mastoideus
12	C4
13	C7
14	T4
15	T8
16	T12
17	L3
18	L5
19	acromion
20	epicondylus lateralis humeri
21	spina iliaca anterior superior
22	trochanter major
23	condylus lateralis femori
24	caput fibulae
25	malleolus lateralis
26	tuberositas ossia metatarsalis V

Figure no. 2. Markers localization on the patient's body.

This point is defined as arithmetic average of points coordinates from anterior superior iliac spines and trochanters (points 2,4,21 and 22 on Fig.2). For each signal after the pre-processing we can draw position, speed and acceleration trajectory for every point. Examples of the signals and their trajectories are presented on figure.3. Position change trajectory for single point n is described along average value $(\bar{x}, \bar{y}, \bar{z})$ described as a signal matrix S(n):

$$\mathbf{S_{(n)}} = \begin{bmatrix} x_1 - \bar{x},\ x_2 - \bar{x},\ x_3 - \bar{x}, \mathrm{K}\ , x_K - \bar{x} \\ y_1 - \bar{y},\ y_2 - \bar{y},\ y_3 - \bar{y}, \mathrm{K}\ , y_K - \bar{y} \\ z_1 - \bar{z},\ z_2 - \bar{z},\ z_3 - \bar{z}, \mathrm{K}\ , z_K - \bar{z} \end{bmatrix}_{3\times K}$$

On base of this we can calculate covariance matrix C, from dependence:

$$\mathbf{C} = \frac{1}{K}\mathbf{S_{(n)}} \cdot \mathbf{S_{(n)}^{T}}$$

Solving characteristic equation of a matrix C we obtain eigenvalues and eigenvectors of the matrix. Eigenvectors show directions of the biggest change in measured data and its coordinates can be used as a parametric measure of vertebral column behaviour in dynamic researches. Researches were made for group of 5 patients. Special software was developed (Stawska, 2006) to allow presentation of the marker's position, velocity and acceleration, as a function of time and its 3D trajectories.

For every patient, original signal can be filtered with an average filter with window's span 3, 5, or 7 samples or Fourier's patients movement model was experimented (Grabowski, 2007). In program's second bookmark, Eigen values, eigenvectors of covariance matrix can be drawn and calculated for every point and every type of signal. Calculations target was also to obtain values of the eigenvectors sum and its directions in Cartesian and spherical coordinates.

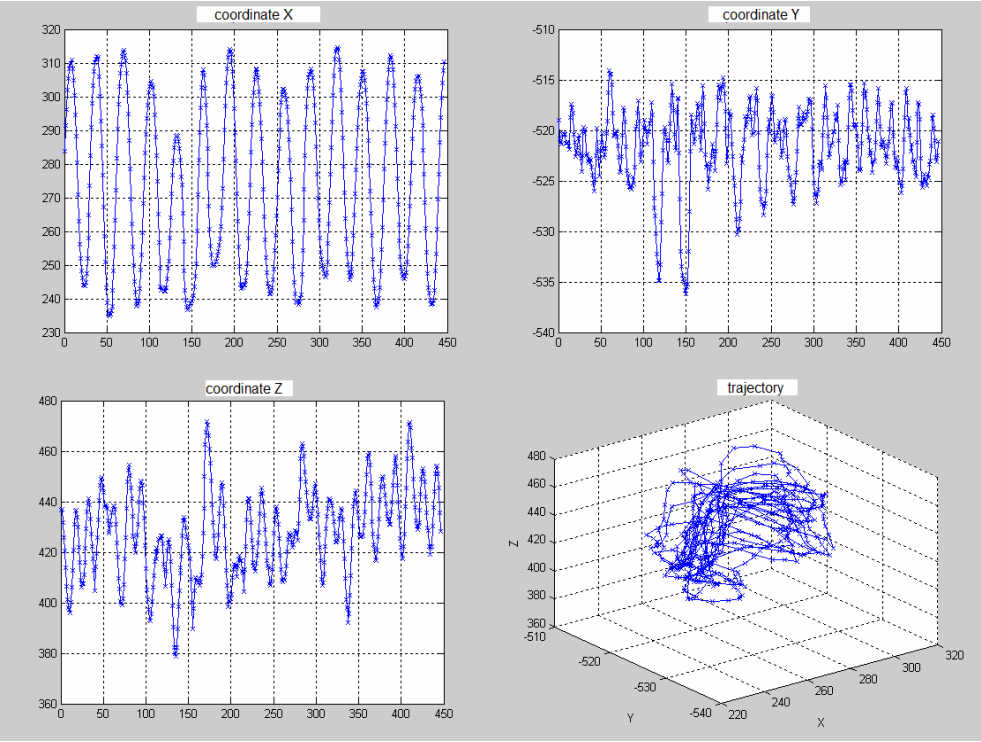


Figure. 3. Position coordinate signals and position trajectory reference to pseudo gravity centre in XYZ space for point no 17 (patient F018).

Results

Example of results for maximum eigenvectors trajectory calculation for points L12, L13, . . . , L18, located on female patient spine F018 are presented in the tables below (in Cartesian and spherical coordinates). These vectors determine the biggest direction changes as the patient walks on the treadmill.

C.	X	Y	Z
L12	-3,04E-04	1,05E-05	4,51E-05
L13	-3,34E-04	7,06E-06	6,01E-05
L14	-2,14E-04	2,82E-06	3,47E-05
L15	-1,38E-04	4,26E-06	4,60E-05
L16	-1,39E-04	2,64E-06	4,74E-05
L17	-1,36E-04	9,45E-07	4,74E-05
L18	-1,27E-04	-7,67E-07	4,55E-05

For this research assumption was made that eigenvector's length is not important and classification is made only on its direction. Main issue in PCA analysis is to determine a difference between the angles of the eigenvectors describing same data. Finding out signal for which PCA vectors have the same direction allows classifying them into groups.

Angles	θ	φ
L12	3.1073	0.1471
L13	3.1205	0.1783
L14	3.1284	0.1606
L15	3.1106	0.3223
L16	3.1226	0.3279
L17	3.1347	0.3346
L18	-3.1355	0.3449

After finding similarities in the groups we can start looking for differences between various groups. In the table we can see angle values between eigenvectors corresponding with the highest eigen values calculated for different kind of data (like shift, velocity and acceleration) for different patients.

Chosen results for all vectors located in defined points of vertebral column can be found below. Data are present for whole group of 5 patients like. F018, F022, M016, M017, M021. The presented data set contain shift (EVVCAt), velocity (EVVCAa) and acceleration (EVVCAa) data for furrier signal model and velocity (EVrawv) for raw (unfiltered) real signal.

Table 1. Direction comparison for corresponding eigenvectors for pairs of patients

	F018 and F022	F018 and M016	F018 and M017	F018 and M021	F022 and M016	F022 and M017	F022 and M021	M016 and M017	M016 and M021	M017 and M021
EVVCAv										
L12	3,00	8,29	6,99	9,11	9,03	8,95	11,02	3,85	4,30	2,12
L13	4,20	8,75	8,86	9,31	11,75	12,74	13,07	4,00	3,47	0,82
L14	28,07	0,57	7,26	3,76	27,74	34,65	29,30	7,78	4,30	5,41
L15	11,05	26,67	27,11	27,13	32,69	35,36	34,42	7,86	4,32	3,60
L16	10,70	30,15	30,73	31,94	34,89	37,28	37,85	6,43	4,66	2,54
L17	13,45	40,77	48,58	38,31	33,66	43,69	32,74	11,44	4,73	10,96
L18	16,39	45,39	57,07	41,05	36,19	48,98	32,71	12,85	4,57	16,42
EVVCAt										
L12	10,37	0,81	5,24	4,97	10,17	8,07	14,42	4,50	4,67	7,03
L13	12,07	1,29	4,70	5,19	12,89	11,87	16,62	4,02	3,99	5,65
L14	30,80	5,51	5,95	5,26	25,63	30,20	34,10	5,81	8,66	4,45
L15	30,98	1,82	9,06	10,06	30,35	28,74	40,34	7,25	10,14	13,20
L16	31,59	1,62	7,50	14,61	32,21	30,24	45,92	6,30	13,76	16,76
L17	29,99	1,22	7,14	14,68	31,18	34,90	44,58	6,23	13,47	10,64
L18	31,44	3,29	8,26	17,24	34,70	39,39	48,66	5,04	13,96	9,43
EVVCAa										
L12	7,38	6,59	3,55	13,82	0,83	10,49	21,05	9,66	20,23	10,58
L13	7,39	4,36	8,77	12,43	3,14	15,90	19,67	12,76	16,54	3,83
L14	116,11	12,09	13,65	32,24	126,71	102,46	84,30	24,94	43,93	19,05
L15	56,30	11,75	38,35	25,62	47,85	94,63	81,90	47,99	35,09	12,91
L16	69,25	14,63	58,43	32,83	57,38	127,67	101,87	70,70	44,82	25,90
L17	95,54	30,64	55,99	161,24	122,96	40,30	101,78	82,74	134,70	141,99
L18	86,60	94,74	64,83	9,82	164,85	151,41	87,14	32,89	96,75	64,92
EVrawv										
L12	14,56	96,49	2,31	4,49	96,12	14,59	11,06	98,79	98,87	3,62
L13	18,03	103,77	3,09	4,89	102,30	18,05	13,96	106,84	105,93	4,09
L14	63,32	84,77	6,74	16,78	97,33	58,97	47,27	80,70	83,70	11,70
L15	61,71	17,85	8,27	11,38	58,68	59,16	51,24	9,66	14,28	8,46
L16	52,80	4,48	7,78	2,79	48,80	58,88	54,59	10,42	5,79	5,06
L17	17,00	33,90	49,90	33,03	46,87	64,50	46,81	18,32	2,86	17,78
L18	25,99	74,85	100,66	38,20	52,57	79,92	14,56	27,44	38,08	65,38

Discussion and conclusion

On the base of received results can be noticed, that analysis and PCA classification for signals without any filtration is impossible. For all analyzed data describing shift trajectory (EVrawt), velocity trajectory (EVrawv) and acceleration trajectory (EVrawa) there is no correlation between patients. Angles between vectors differ a lot and we cannot find a single pair of patients with any correlation for PCA vectors. Real, unfiltered signal cannot be a base for PCA analysis. This is a result of small signal resolution in time, what leads to a little precise trajectory reconstruction. It is liable for noises. Next problem is measurement errors which can be partly eliminated using VCA model. Origin of those errors is patients walk manner, like different steps length, jumps, and movement on the belt during examination. Looking at the filtered or Fourier's model data (VCA) some correlations can be observed for all male patients and we can see difference between the opposite sexes. Vectors calculated from VCA model show that there is correspondence between some of them in all observed cases.

All patients have similar angle from the vectors generated basing on vertebras no. C4, C7. In examinations of two women there is no correlation for vectors from vertebra no. T4. Explanation for that anomaly is that the patient no. F022 previously diagnosis, showing spine disorder. Use of Principal Component Analysis (PCA) for dynamic vertebral column examinations allows parameterization and compression of big data sets. Vertebral column of an examined patient can be described by 21 or even 14 parameters being data for automatic classification tools or be treated as a behaviour template. It seems that PCA analysis can be an efficient data classification tool, but to be able to handle this analysis signal pre-processing has to be done. Signal modelling using Fourier's models (model VCA), or in a lesser degree his filtration, allow to carry out filtration separating common futures in vertebral column dynamics. That can allow us to develop an economic screening system for the early diagnosis of spine deformities without the use of x-rays and adding advantages such as a dynamic evaluation of the gait related to the movement of the spine. Our results are promising.

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KORIŠTENJE PCA ZA PARAMETRIZACIJU DINAMIČKIH PREGLEDA KRALJEŽNICE

Sažetak

Glavna svrhe ove teze je opisivanje metode za parametrijsku analizu ljudskog hoda. Mjereni podaci su prikupljeni stereovizijskom tehnikom. Za prikupljanje podataka, registirani su položaji pozicijskih markera na ljudskom tijelu. Parametrizacija je izvršena preko eigenvektora matrice kovarijanci pozicija, brzine i ubrzanja kalkulacije trajektorije za svaki od markera. Pripremljeni software dopušta filtraciju signala, vizualizaciju trajektorije i neophodno izvođenje kalkulacije. Fourierovi modeli kretanja pacijenta također su korišteni u istraživanju. Vrednovanje, preprocesiranje i 3D rekonstrukcija su provedeni na brojnim studentima Sveučilišta u Valenciji, a rezultati su elaborirani na Varšavskom Tehnološkom Sveučilištu.

Ključne riječi: *stereovizija, kralježnica, dinamika, eigenvalues, eigenvektori*

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