

CLASSIFICATION OF CHRONIC WHIPLASH ASSOCIATED DISORDERS WITH ARTIFICIAL NEURAL NETWORKS

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Abstract - This study present a new method for classification of subjects suffering from Whiplash Associated Disorders (WAD) with a supervised resilient Back Propagation Neural Network (BPN). The only input needed, from each subject, is features extracted from 3-dimensional motion data collected by a ProReflex system.

The analysis with BPN results in a correct prediction for 84% of normal subjects and 89% percent of subjects with WAD.

Keywords - Whiplash Associated Disorder, Principal Component Analysis, Back Propagation, Neural Network, Motion analysis, Helical angle, Prediction

I. INTRODUCTION

Every year there are 16000 car accidents in Sweden, which lead to WAD. Out of these accidents, about 1500-2000 victims get symptoms that lead to medical invalidity [7]. WAD is principally caused by rear-end collisions or accidents where energy is transferred to the neck during the event. This trauma may lead to injuries in the structures of the cervical spine, nerve roots and the central nervous system. Most of the victims recover after 1-14 weeks [6]. In some cases, the suffering is prolonged and leads to permanent disability. Primary damage of tissue is frequently not revealed by standard X-ray. Instead other imaging techniques e.g., MRT can in some instances show changes [10]. Despite absence of abnormal imaging findings, patients can suffer from WAD.

Subjects with WAD show distortion in neck movement pattern after a whiplash injury, e.g., in active range of cervical motion, velocity, proprioception and reaction time [2], [3], [4]. Thus, an objective motion analysis would improve the clinical diagnosis and could serve as screening before using more expensive methods.

Often, it is not sufficient studying a single feature, e.g., active range, when evaluating WAD [11]. The question is how to analyse a multiple of features in an appropriate way. Different Artificial Neural Networks (ANN) have been developed during the past ten years to handle big and multivariate data quantities. Bishop et al. [1], used a radial basis function network which successfully predicted motion patterns from subjects with Low Back Pain (LBP). Since WAD and LBP have similar symptoms and are related to the spine, it is likely that an ANN approach can be used for prediction of WAD.

The aim of this study was to evaluate whether or not it is possible to predict a subject as normal or with chronic WAD with respect to the neck movement pattern. A regular

feedforward ANN with supervised learning is used for prediction as indicated by Bishop.

II. METHODOLOGY

Two groups, including 19 normal subjects (without any neck or back problem) and 55 subjects suffering from WAD, were selected for this study as illustrated in Table 1. All subjects with WAD (with different degrees of injury) had their diagnoses made by a physician. This study was performed 10 months after the injury on average. Informed consent was obtained from each subject and the local ethics committee approved the study.

The method is based on collecting movement pattern, during simple head movements (flexion-extension and axial rotation), from every subject with ProReflex (system made by *Qualisys AB, Sweden*). Each subject repeated every head movement 4 times in a random order, resulting in 16 head movements in total. The subjects were instructed to perform the movements to a comfortable extent and as fast as possible. In order to measure the reaction time the movements were initiated by a visual arrow (placed on a board in front of the subject) pointing in the desired direction of movement, as illustrated in Fig. 1. The instructions were recorded on tape, in order to give all subjects the same information. Circular retro-reflective markers, 3 on the head and 3 on the chest (to compensate for shoulder movements), were used for collecting 3-dimensional co-ordinates for each subject, as illustrated in Fig. 1.

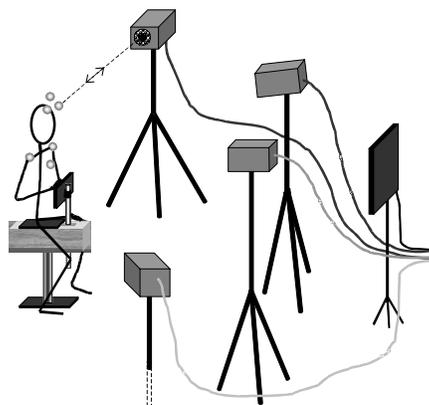


Fig. 1. Illustrates the experimental set-up. Subject has retro-reflective markers on shoulders and head, and performs neck movements as instructed. An arrow shown on the board, on the right of the picture, initiates the desired movement. Pulses of IR-light are emitted from the cameras, which also sample IR-light, at 60 Hz, reflected by the retro-reflective markers.

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Each retro-reflective marker was sampled with 60 Hz. The 3-dimensional co-ordinates were used for calculating a number of features (e.g., neck range, velocity, reaction time, etc.) for each head movement and subject, as shown in Table 2. In order to compare data from different subjects a method by Spoor and Veldpauw [12] was used for calculating the rotation around the helical axis. This method requires 3 non-linear markers in order to calculate the rotation. All features were measured relatively to the helical angle after compensating for shoulder movements. For each type of head movement (flexion, extension and right and left axial rotation) the mean value for each feature was calculated, resulting in a 20-dimensional vector describing one subject. This procedure was repeated for each subject, resulting in a matrix as illustrated in Fig. 2.

The matrix was used as input to the Principal Components Analysis (PCA) for pre-processing and data reduction, as described by [9]. 99 percent of the total variance was explained by the first 10 Principal Components (PC), which were used as input to the BPN. A trained and optimised BPN (illustrated in Fig. 3) classified every subject (using the vector of features), either as normal or with WAD, according to the prevailed method, described in [8]. In order to optimise the BPN 240 different network configurations were tested, containing one or two hidden layers with a maximum of 15 neurones in each layer. The smallest BPN contained one neurone in a single hidden layer and the largest contained 30 hidden neurones divided into two hidden layers.

Each network was trained and tested in the following way: One 10-dimensional test vector was picked (from one subject). The remaining input vectors were randomly divided in two data sets: 55 vectors for training and 18 vectors for validation. The training algorithm ended when the summed squared error, for the validation set, started to increase. In order to get a classification for every subject this procedure was repeated for every subject in this study. MATLAB, from MathWorks Inc., was used for carrying out the PCA and the BPN method.

	Feature 1	Feature 2	Feature N
Subject 1	Vector of features describing subject 1			
Subject 2	Vector of features describing subject 2			
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Subject M	Vector of features describing subject M			

Fig. 2. Matrix containing features calculated for each subject, where M stands for total number of subjects and N for total number of features (M=74 and N=20).

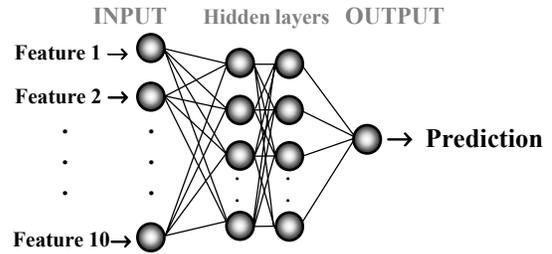


Fig. 3. A feedforward network with two hidden layers containing 10 respectively 7 neurones was used. Hyperbolic tangent sigmoid transfer functions were used for weights in hidden layers, and log sigmoid transfer functions were used for weights in the output layer. The network was trained with supervised learning by resilient backpropagation.

III. RESULTS

The PCA resulted in a component score, as shown in Fig. 4, which indicates a certain overlap between motion patterns from normal subjects and subjects with WAD.

Testing with BPN resulted in a correct prediction for 84% of normal subjects and 89% percent of subjects with WAD, as shown in Fig. 5.

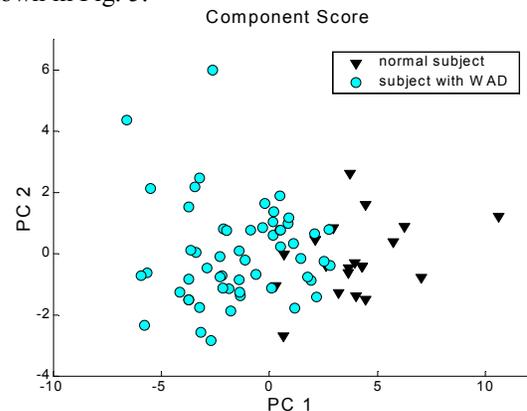


Fig. 4. Illustrates a 2-dimensional component score. Circles represent subjects with WAD and triangles represent normal subjects (10 PC were used when making the prediction with BPN).

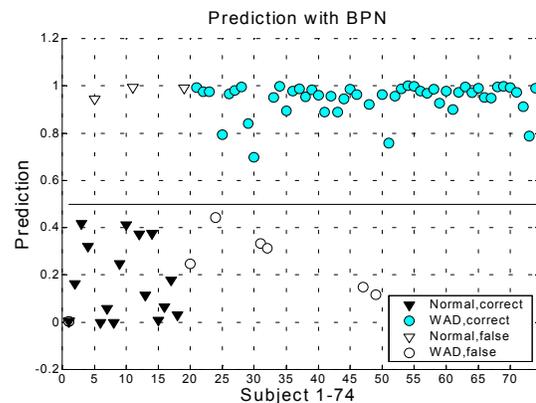


Fig. 5. Result from prediction with BPN. Since log sigmoid transfer functions were used in the output layer, the output range is between 0 and 1. Output ≥ 0.5 indicates WAD and output < 0.5 indicates normal neck movement. 16 of 19 normal subjects (filled triangles to the left) and 49 of 55 subjects with WAD (filled circles to the right) were correctly predicted. Open triangles and circles represent subjects with false prediction.

IV. DISCUSSION

This paper describes a software-based method for prediction of subjects suffering from WAD. The advantage in using a BPN, for multivariate data sets, is the non-linear supervised learning algorithm. This behaviour makes it easier for the network to follow non-linear clustering the data set.

The data collection and BPN equipment is relatively cheap compared to other health care systems (e.g., MRT, also used for evaluating WAD patients). It is based on a desktop computer and the motion analysis system, i.e., ProReflex.

The method is easy to use for the clinician and may be used for basic screening. The rehabilitation progress can also be monitored with this method for patient follow-up.

In order to grade WAD, more features and movements must probably be added, e.g., movements indicating the subjects' proprioception. Some patients mentioned that the selected movements (flexion-extension and axial rotation) had no negative effects on their neck motion.

This method has improved the ability to diagnose WAD and need to be further developed to fit the demands of the healthcare.

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TABLE 1
DESCRIPTION OF 74 SUBJECTS

Classification	Male	Female	Average age (standard deviation)
No neck pain	10	9	37.5 (10.5)
WAD	28	27	38.4 (10.3)
Total	38	36	

TABLE 2
FEATURES EXTRACTED FROM MOTION DATA,
MEAN ± STANDARD DEVIATION

	Extension	Flexion	Right rotation	Left rotation	
v_{max}	185 ± 61	223 ± 64	324 ± 93	325 ± 80	Normal
[°/s]	78 ± 44	94 ± 47	157 ± 72	160 ± 69	WAD
v_{mean}	48 ± 18	56 ± 14	78 ± 32	79 ± 29	Normal
[°/s]	20 ± 11	26 ± 13	40 ± 19	39 ± 18	WAD
Θ	46 ± 8	62 ± 11	72 ± 8	72 ± 8	Normal
[°]	30 ± 12	40 ± 15	55 ± 16	55 ± 15	WAD
r	0.35±0.08	0.37±0.10	0.33±0.08	0.32±0.09	Normal
[s]	0.45±0.10	0.42±0.09	0.42±0.11	0.40±0.10	WAD
S_{θ}	0.020 ± 0.016		0.015 ± 0.013		Normal
	0.038 ± 0.046		0.022 ± 0.019		WAD
S_v	0.036 ± 0.034		0.029 ± 0.034		Normal
	0.053 ± 0.046		0.055 ± 0.054		WAD

v_{max} - maximal angular velocity, v_{mean} - mean angular velocity, Θ - range of motion, r -reaction time, S_{θ} - symmetry of movement range and S_v - symmetry of mean angular velocity. Symmetry is defined as a dimensionless diversity in range and angular velocity

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