An Intelligent Clinical Decision Support System for Analyzing Neuromusculoskeletal Disorders

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Abstract. This study presents a clinical decision support system for detecting and further analyzing neuromusculoskeletal disorders using both clinical and gait data. The system is composed of a database storing disease characteristics, symptoms and gait data of the subjects, a combined pattern classifier that processes the data and user friendly interfaces. Data is mainly obtained through Computerized Gait Analysis, which can be defined as numerical representation of the mechanical measurements of human walking patterns. The decision support system uses mainly a combined classifier to incorporate the different types of data for better accuracy. A decision tree is developed with Multilayer Perceptrons at the leaves. The system is planned to be used for various neuromusculoskeletal disorders such as Cerebral Palsy (CP), stroke, and Osteoarthritis (OA). First experiments are performed with OA. Subjects are classified into four OA-severity categories, formed in accordance with the Kellgren-Lawrence scale: "Normal", "Mild", "Moderate", and "Severe". A classification accuracy of 80% is achieved on the test set. To complete the system, a patient follow-up mechanism is also designed.

1 Introduction

Gait analysis is the process of collecting and analyzing quantitative information about walking patterns of people. Gait analysis finds applications in medicine and enables the clinicians to differentiate gait deviations objectively. It serves not only as a measure of treatment outcome, but also as a useful tool in planning ongoing care of various neuromusculoskeletal disorders such as cerebral palsy, stroke, OA, as an assistive tool to other approaches such as X-rays, magnetic resonance imaging (MRI), chemical tests etc. Gait process is realized in a 'gait laboratory' by the use of computer-interfaced video cameras to measure the patient's walking motion, by the use of surface electrodes placed on the muscles to follow muscle activity, and by the use of force platforms embedded in a walkway to monitor the forces and torques produced between the subject and the ground. Resultant data (such as knee angle/time) is tabulated in graphic/numerical forms by commercial software. Kinetic and kinematical temporal changes during walking are also obtained. In addition to temporal changes of joint angles and force data, time-distance parameters of the gait such as velocity, cadence, stride length, step length are recorded. It is not possible to predict the resul-

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tant biomechanical musculoskeletal characteristics using other approaches such as radiographic evaluations, which makes gait analysis a preferable tool.
Non automated decision making from gait data requires high level of expertise of neuromusculoskeletal system trained for the purpose. An automated system is expected to decrease this requirement by a 'transformed knowledge' of these experts. Automated gait analysis in medicine may also be used as a consultative and educational tool.

A clinical decision support system (CDSS) may be used for many medical applications [13-17] but CDSS's for deseases that use gait data are new. There are studies in which pattern recognition algorithms are used to distinguish 'healthy' from 'pathological' gait. Most popular of these algorithms are neural networks (NNs) [1-4] and support vector machines (SVMs) [4]. Most of these studies are implemented by a limited number of subjects (less than 20) and by using manually selected gait features. Since gait data is high dimensional and complex, to design a complete decision support system may require a combination of all available features. In fact, physicians make decisions about the illnesses by interpreting all available data in traditional systems.

Most of the previous gait analysis systems ignore history and symptoms of the patient, such as age, pain grade, family history. Recently, the focus has been on combining several classifiers and getting a consensus of results for better accuracy for similar cases [5, 6]. Today, combining methods are preferred for many well known pattern recognition problems such as character recognition and speech recognition.

Automatic feature selection from many numerical gait parameters is another subject that's not studied well. Actually, there are many medical practices testing the variations which are caused by the related illness in the gait attributes [7-9]. Selection of attributes is usually done by using the result of these studies by expert clinicians. However, the judgments may vary in different experts leading to the different interpretations. Obviously, automated selection lessens the dependence and the load on the experts

The main objective of this study is to design an intelligent CDSS, namely OAGAIT, to grade and further follow the progress of OA as a neuromusculoskeletal disorder. Moreover, the design of a complete gait database that is adaptable to any data collection software in the gait laboratory is in the scope of this study. Symptoms and history of the patients and automatically selected numeric gait data are combined using a multi-classifier approach.

The remainder of the report is organized as follows. Section 2 introduces the data collection process and the characteristics of data. This is followed by details of feature selection process and classifier combination. Then the next section gives information about the experiments and their results. Conclusions are presented in the last section.

2 Data Collection

In this study, the gait data are collected by the gait experts in Ankara University Faculty of Medicine, Department of Physical Medicine and Rehabilitation Gait Laboratory. The symptoms and history of the patients are also collected in the lab before the patients are walked. Collected information other than gait is converted to numerical values before they are used as features. Then, the first subset of the data can be defined as:

A = {age, BMI, pain, stiffness, history, period}

Subjects undergo gait analysis with the same protocol by one and the same physician. Skeletal movement can be described using surface markers placed in precise anatomical positions. All subjects are instructed to walk at a self selected speed along the walkway and to practice until they can consistently and naturally make contact with both of the force plates. Time-distance parameters of the gait are gathered at the end. So the second set of the data is composed of time distance parameters (Set B):

B = {Cadence, Walking Speed, Stride Time, Step Time, Single Support, Double Support, Stride Length, Step Length}

External retro-reflective markers are placed on each of the following anatomical locations: anterior superior iliac spine (ASIS), sacrum, lateral thigh, joint line of the knee, lateral shank, calcaneus, lateral malleolus and second metatarsal head. Ground reaction forces (GRF) are collected using 2 force plates. Moments and powers are calculated by using GRF data. Then the final subset of the data includes 33 gait attributes which are defined as the temporal changes of the joint angles (Set C).

C = {PelvicTilt, Pelvic Obliquity Knee Flexion, Knee Varus, … }

Each of these attributes in C above is represented by a graph that contains 51 samples taken in equally spaced intervals for one gait cycle. So the attributes for a given subject can be arranged as a 33x51 dimensional array X as below:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} \cdot\cdot & \cdot\cdot x_{1,51} \\ : & : & : \\ x_{33,1} & x_{33,2} \cdot\cdot & \cdot\cdot x_{33,51} \end{bmatrix}$$

Where $x_{i,j}$ is the value of the $\mathbf{i^{th}}$ gait attribute at $\mathbf{j^{th}}$ time period of the gait cycle.

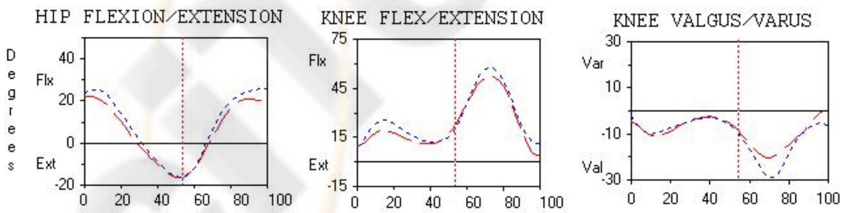

Fig. 1. Examples to temporal gait attributes (data set C): The data is reported in 2-D charts with the abscissa defined as the percentage of the gait cycle time and the ordinate displaying the gait parameter.

Figure 1 shows examples of the graphical representation of the temporal changes of the joint angles with 51 samples in each graph taken for one stride. A complete database is designed and integrated to data collection software to keep them together and to access easily when needed.

2.1 Feature Reduction and Selection

A basic feature reduction technique was applied before a selection process was used. Initially, the dimensions of all attributes are reduced from 51 to 5, by taking means of 10 consecutive time samples. The feature space still has a too high dimension (5x33), which forces the elimination of the redundant attributes. The Mahalanobis Distance is used as a selection criterion, which may result with correlated attributes in general. However, since our data is from different motion planes and different anatomic levels of the body, correlation between the selected ones is not very probable. The number of selected attributes is limited to the best ratio of the number of subjects and the number of features, which is suggested as one over five in [10, 11]. Table 1 shows the classes (i.e. grade of the OA) that datasets include and the selected gait attributes for those datasets.

Table 1. Selected gait attributes for each two class case (P: Pelvic, F: Foot, H: Hip, K: Knee, Flex: Flexion, M: Moment, Tot: Total, Dor: Dosrflexion, Rot: Rotation, Val: Valgus, Obliq: Obliquity, Adb: Abduction). The classes are the severity levels of OA, as explained before.

Classes	Selected Gait Attributes					
0-1	**F**.M.Dor	**H.**Flex	**K**.M.Flex	**K**.Flex	**P**.Tilt	**F**.Rot
1-2	**K**.Flex	**K**.M.Flex	**K**.P.Flex	**H**.P.Tot	**K**.P.Tot	**K**.Val
2-3	**H**.P.Abd	**H**.Flex	**A**.P.Dor	**H**.Rot	**H**.P.Flex	**K.**Val
1-3	**K**.P.Flex	**K**.P.Tot	**K**.Flex	**P**.Obliq	**K**.M.Rot	**K**.Val
0-2	**F**.M.Dor	**K**.Flex	**H**.Flex	**F**.Dor	**K**.Rot	**P**.Tilt

In the next stage, these gait attributes are used for creating input vectors for the related expert MLP. Listing these attributes gives some valuable information about progress of the OA.. For example, while knee related attributes seen more frequently in dataset composed of classes 1 and 2, hip related ones seem more discriminative for classes 2 and 3. This shows that as the grade of the illness increases hip angles are affected more. This kind of information is valuable for clinical decision making and training physicians.

3 Classification using Decision Tree MLP Multi-Classifier

It is difficult to combine different features as continuous variables, binary values, and discrete labels into a single representation. Therefore, the combination of multiple classifiers is a good solution for a problem involving a variety of features. In this study a Mixture of Decision tree classifiers and Multilayer Perceptrons that are experts for different regions of the feature space are used for classifying four levels (0 to 3) of knee Osteoarthritis. The approach is similar to the Mixture of experts combined classifier method [5]. The accuracy of the proposed system will be safeguarded by using all feature sets A, B, C above with Kellgren score-labeled subjects.

The learning and classification processes consist of two stages. In the first stage a decision tree is trained by using data set A and B as shown above. In the second stage, the samples in every leaf are analyzed for feature selection and an expert MLP is trained by composed datasets using attributes from set C to classify the data into one of the two categories 0-1, 1-2 etc..

This approach uses three recognizers with 2 categories each instead of a recognizer for four-categories, using expert neural networks for discriminating neighbor classes. The basic classifiers used in the leaves of the decision tree are MLPs. Three- layered (one hidden layer) MLPs are trained by different input vectors. These input vectors are trained by automatically selected gait attributes, different for each leaf as mentioned above. So, they are assumed to be experts in the region of the binary decision of the category. Figure 2 summarizes the proposed combination in a simplified form, where

- **$Y = \{y_1, y_2, \ldots y_n\}$** is the union of set A and B above
- **$T = \{t_1, t_2, \ldots t_n\}$** is the set of corresponding threshold values for above, used for composing tree.
- **$X= \{x_1, x_2, \ldots x_m\}$** is the set of datasets composed by selected attributes of set C and presented to the expert networks as input

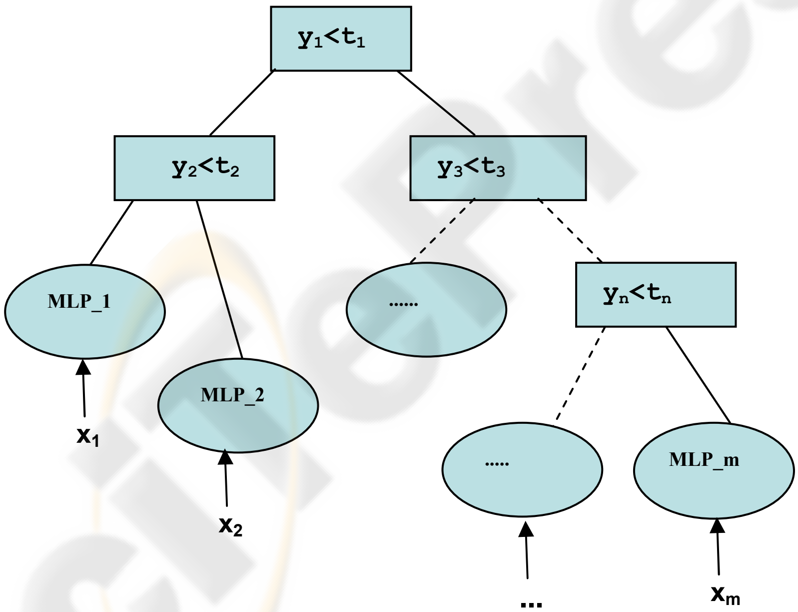

Fig. 2. Proposed example combination in a simplified symbolic representation.

3.1 Implementation and Results

The training of our combined algorithm has two parts, decision tree training and training of MLP's. In decision tree trainers, topology is created first and then training data is presented. Decision tree construction and training processes can not be considered separately. Tree is constructed according to the training data set by using some predefined criteria. *Splitting* and *stopping* criteria are important for constructing the best tree representing the training set and avoiding overfitting. Here, Gini index impurity is used for splitting.

Pruning step of the tree construction is done by considering the structure of the combination. This means that a method to prune the tree so that each leaf has samples from two classes was used.

In the next stage of the combination process, MLP's responsible for discriminating these two classes are replaced by the related leaf. These MLPs are responsible for discrimination of classes 0-1, 1-2 and 2-3 respectively. They are trained by *bpxnc* property of the PRTools [12]. This function creates a feedforward neural network and uses Backpropagation algorithm for training. MLP's have three-layer structures with binary outputs. They are tested by crossvalidation approach and an average error rate for each is gathered as shown in Table 2.

Table 2. Classification errors of MLPs.

MLP	Classes (grades)	Classification error (%)
MLP1	0-1	11
MLP2	1-2	16
MLP3	2-3	21

Then the algorithm is tested by an unseen dataset composed of 20 samples and a correct classification ratio of %80 is achieved, as shown in confusion matrix in Table 3. The reason for most of these misclassified subjects is that they have been assigned to wrong expert MLP in the decision tree. This wrong assignment is mostly because of the pain level feature, which is a subjective feature determined by the subject himself. For example, a subject from grade 1 can determine his pain level as 10 (max value for pain level) while the other from grade 3 can say 3. These kind of subjective features are not preferred in classification processes but experts and medical studies in literature show that pain level is one of the important indicators of the selected illness, so it is used here anyway.

Table 3. Confusion matrix for combination (test data).

		Estimated Classes					
		0	**1**	**2**	**3**	**total**	**error rate**
Actual Classes	**0**	18	2	0	0	20	0,1
	1	1	15	2	2	20	0,25
	2	0	1	17	2	20	0,15
	3	0	2	4	14	20	0,3
	total	19	20	23	18	80	**0,2**

Finally, for comparing the success of our combination schema with a single MLP classifier, a four-class neural network is trained. A three layered MLP, call it MLP4, is created. The same feature reduction and selection processes are applied to this new dataset. The estimated labels are gathered as an output of crossvalidation algorithm. The classification rate of the MLP4 which is about %58, proved us that using different experts for different part of the feature space and then combining produced better results.

4 Clinical Decision Support System

CDSS's can be defined as interactive computer programs assisting physicians and other health professionals with decision making tasks. The basic components of a CDSS include a medical knowledge base and logical rules derived from experts. There are many computer applications designed to be a CDSS. Programs that perform database search or check drug interactions support decisions, but usually they are not called CDSS. In [13] a CDSS is defined as a program that supports a reasoning task, implemented behind the user interfaces and based on the clinical data.

Today, medical experts' desire for computer usage in clinical applications, the need for rapid access to recent information and the need for time saving increases the number of commercialized CDSSs. Other potential benefits of using CDSSs in clinical practice are grouped in three broad categories [16]: Improved patient safety, improved quality of care, improved efficiency in health care delivery.

DXplain, QMR, ERA and ATHENA are good examples of successful systems originating after 80s [13-15]. In [17] the authors systematically reviewed the literature published up to 2003 to identify features of CDSSs critical for improving clinical practice. Table 4 shows most significant 15 of these features of CDSSs as compared to OAGAIT. It can be concluded that OGAIT classifies as a good CDSS.

Table 4. Features of OAGAIT compared to the ones suggested in [17].

Features of a good CDSS	Features of OAGAIT
General system features	
Integration with charting or order entry system to support workflow integration	Integration of OAGAIT and VICON system
Use of a computer to generate the decision support	Fully computerized decision support
Clinician-system interaction features	
Automatic provision of decision support as part of clinician workflow	When the subject's gait data is entered to the database the grading info is automatically displayed on the screen.
No need for additional clinician data entry	All needed data is entered to the database before processing
Request documentation of the reason for not following CDSS recommendations	There is a additional notes entry in all forms
Provision of decision support at time and location of decision making	The grading results are shown on the screen just after the walking of subject
Recommendations executed by noting agreement	Not applicable

Table 4. Features of OAGAIT compared to the ones suggested in [17] (cont).

Communication content features	
Provision of a recommendation, not just an assessment	OAGAIT supply reasoning for the assessment to help creation of treatment plans
Promotion of action rather than inaction	OAGAIT produces most probable two classes as a result rather than "not classified" message.
Justification of decision support via provision of reasoning	OAGAIT shows assessment stages to support reasoning
Justification of decision support via provision of research evidence	The decision tree property of OAGAIT supplies research evidences for provision of OA
Auxiliary features	
Local user involvement in development process	An expert physician is included in the development process as both an knowledge expert and end user
Provision of decision support results to patients as well as providers	Physician is responsible for delivering the results to the patients
CDSS accompanied by periodic performance feedback	Not applicable
CDSS accompanied by conventional education	A short training is given to the physicians and/or other laboratory staff

The system has easy-to-use user interfaces, so a short training is enough for the physicians and/or other laboratory staff. It has a short processing time; the grading results are shown on the screen just after walking of the subject, which provides an immediate feedback.

5 Conclusions

OGAIT, a software for grading and further analysis of the knee OA was studied as a part of a CDSS for neuromuscular disorders. Main aim of OAGAIT is to interpret gait data almost as close as an expert's. This interpretation is done by using expert knowledge on gait and features of pattern recognition. OAGAIT supports the function of radiographic films for grading of OA and/or other diseases. It has a complete gait database integrated with the data collection software. This database combined all new and old gait data in an easy access and portable environment. Moreover, this database is convenient to use for further studies about other diseases or integration to other software systems.

This study presents a new approach for estimating Kellgren-Lawrence grades of the subjects by using only gait data and patient history with an accuracy rate of 80%, which is found to be very successful as a clinical test by the M.D.'s. Moreover, data analysis process indicated relations of severity of the OA to the joints affected by gait adaptations. We proved the hypothesis that the reduced motion of the knee joint is compensated by an increased motion of the hip joint.for the patients with the advanced OA.

The classification success of the implemented combining classifier was compared with the generalization accuracy with a single uncombined MLP. It can be concluded that our algorithm performed significantly better and supplied some additional advantages such as reasoning about the disease level is possible using this approach.

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