P 83 Classification of Vibroarthrography Signals from Equine Fetlock Joints

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Abstract:
Durch die Aufzeichnung von Vibrationen (Vibroarthrographie), die bei Gelenkbewegung entstehen, versprechen sich Veterinärmediziner eine vereinfachte Diagnose von Gelenkkrankheiten. Eine Methode zur Analyse solcher Signale hinsichtlich des pathologischen Zustandes von Fesselgelenken des Pferdes wird vorgestellt. In einem Local-Dicriminant-Bases-Algorithmus werden die Koeffizienten einer Wavelet-Paket-Transformation für Trainingssignale berechnet und anschließend wenige aussagekräftige Koeffizienten mithilfe einer Diskriminanzbewertung identifiziert. Diese Koeffizienten bilden die Grundlage für eine Klassifikation bezüglich des pathologischen Gelenkzustandes mittels lokaler Diskriminanzanalyse. Der Ansatz ermöglicht eine exakte Bewertung vorliegender Signale.
Recordings of vibrations appearing during joint movement (vibroarthrography) shall facilitate the diagnosis of joint diseases. A method is introduced to analyse vibroarthrography signals from equine fetlock joints regarding their physical condition. In a local discriminant bases algorithm, significant coefficients of a wavelet package transform using training signals are selected by evaluating their discriminance properties. These coefficients build a basis for a classification of the joint condition using local discriminance analysis. This approach enables an exact evaluation of actual signals.

Introduction: Vibroarthrography records inner joint vibrations caused by inner joint friction. The signals are influenced by pathological processes. The aim of this screening is to determine the joint health without costly medical imaging [1]. For vibroarthrography signals from equine fetlocks joints, evaluation methods have to be developed. In human medicine, vibroarthrography signals from the knee can be classified by the local discriminant bases (LDB) approach [2]. This approach is adapted to signals of high duration, which is typical for vibroarthrography signals, where recording times are typically several seconds. Based on a generalized LDB approach [3] we developed a method to detect diseased and healthy fetlock joints.
The LDB approach uses a wavelet package transform to provide a very fine signal analysis by considering approximation and detail coefficients with both short and long time support [3]. To reduce the number of wavelet coefficients, they are rated by their discriminance properties regarding the signal classes. A local discriminant analysis is applied on these coefficients. This allows for a fast signal classification with low computational cost.

Material and Methods: At the *Stiftung Tierärztliche Hochschule Hannover*, ten vibroarthrography signals were recorded from diseased und healthy equine fetlock joints each. During a manually evoked periodic movement of the joint, signals were recorded with a sampling frequency of 44.1 kHz. Each signal is ten seconds long and contains five periods of evoked movement [1]. For illustration, two signals are shown in Fig. 1. Each signal was split into 39 equidistant parts of 10,772 samples each for precise evaluations [4].
For a precise signal analysis, the vibroarthrography signals are decomposed by a wavelet package transform. It is based on a wavelet package library that contains two kinds of basis vectors. One kind of vectors is used to approximate the signal and the other basis vectors represent details missed by the approximation. A wavelet package transform can be interpreted as a binary tree. Its root node contains the original signal $\boldsymbol{w}_0 \in \mathbb{C}^N$ with $N \in \mathbb{N}$ being the signal length [4]. To fill a child node, its corresponding basis vectors in the wavelet package library are multiplied with coefficients $\boldsymbol{w}_j^{\boldsymbol{i}}$ of the mother node $\boldsymbol{i}$. At every split node $\boldsymbol{i} \in \{0,1\}^j$ in level $0 \leq j < J$, the coefficients $w_{j+1}^{(i,0)}, w_{j+1}^{(i,1)}$ for the two child nodes of the binary tree are calculated by

$$\begin{pmatrix} A \\ D \end{pmatrix} w_j^i = \begin{pmatrix} w_{j+1}^{(i,0)} \\ w_{j+1}^{(i,1)} \end{pmatrix}.$$

The approximation and detail matrices A, D of size $2^{m-j} \times 2^{m-j+1}$, $N = 2^m$, contain the basis vectors that are scaled in time with the tree depth to represent coarser signal approximations [5]. The nodes are filled up to a maximum tree depth $J \in \mathbb{N}$.
A wavelet package transform generates a huge amount of wavelet coefficients but an analysis is sought that is computable on small devices. Therefore, only a few of those wavelet coefficients are selected by the following method to maximize the class discriminance [3].
The training of the LDB approach starts with all wavelet package coefficients and in a first step, a subtree is searched that presents a basis with high class separation properties. This subtree is generated by calculating the symmetric Kullback-Leibler divergence of each node [3]. To minimize later computional cost, the amount of basis vectors is further reduced by evaluating Fisher's class separability for all coefficients of the subtree [6]. So, only the coefficients belonging to the basis vectors with highest discriminance properties are used to train a local discriminant analysis (LDA) classifier [4,7]. Once the training of the best basis vector for class separation is done, only the corresponding coefficients have to be computed with low cost.

Result: The LDB was trained using empirically choosing Daubechies wavelets with five vanishing moments as library and a tree depth of $J = 5$ [4]. To evaluate the influence of the number of finally selected basis vectors, the number was differed from 1 to $5{,}386$. To offer high resolution, each of the 39 signal parts was trained in an isolated fashion. As error measure, the number of false classifications was calculated using the leave-one-out method [8]. Fig. 2 displays the classification error for each signal part depending on the number of basis vectors used in the LDA.
The illustration in Fig. 2 shows the classification results of the introduced approach for the vibroarthrography signals from equine fetlocks. With the proposed LDB algorithm, it is possible to classify those signals correctly. Using only a few number of basis vectors, perfect classification is reached on specific signal parts. Considering all parts of a signal, a correct decision on the pathological condition of the equine fetlock is possible.
Signals do not necessarily have to be recorded with full ten seconds length. Even with the information gained within the first periods of joint movement, the classification results are exact. Also, a number of basis vectors used for classification higher than ten results in less accuracy. So, only a small number of basis vectors are necessary which reduces computational cost [4].

Conclusion: An automated classification of vibroarthrography signals from equine fetlock joints is shown. The local discriminant bases algorithm yields a wavelet package basis with high discrimination power. Not more than ten wavelet coefficients are necessary to exactly classify those signals.

Appendix 1

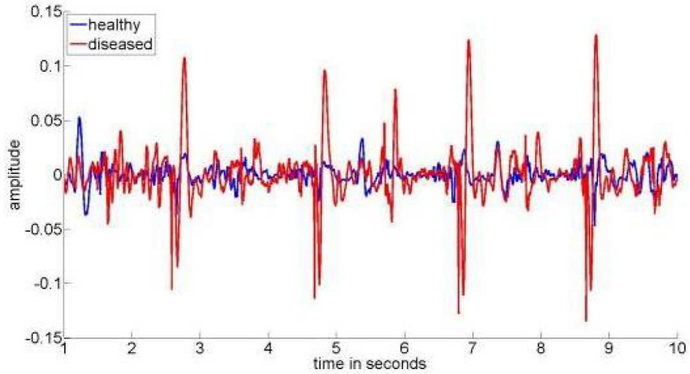

Fig. 29: Two examples of signals recorded from healthy and diseased joints.

Appendix 2

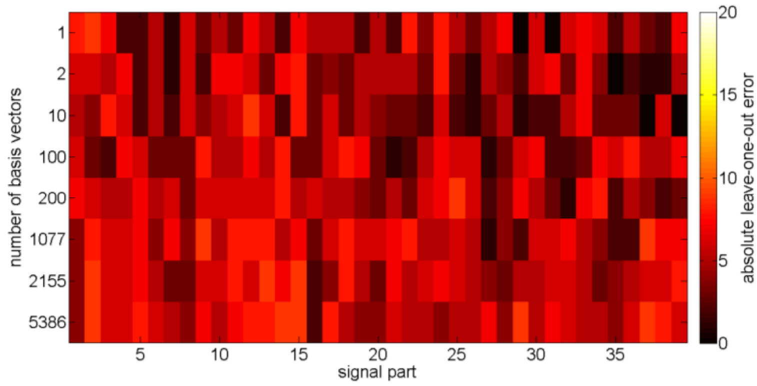

Fig. 30: Classification error per signal part depending on the number of best basis vectors used for LDA.

Literature

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