A Systematic approach to improve Support Vector Machine applied to ultrasonic guided wave spectrum image classification

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***Abstract*—Osteoporosis is a skeletal disorder characterized by low bone mass, which compromises its resistance and increases the risk of fractures, and is a widespread problem worldwide. Currently, the gold standard for assessing fracture risk is the measurement of the areal bone mineral density with Dual-Energy X-ray Absorptiometry. Several ultrasound techniques have been presented as alternatives. It has been shown that the estimation of cortical thickness and porosity, obtained by Bi-Directional Axial Transmission, are associated with non-traumatic fractures in postmenopausal women. Cortical parameters were derived from the comparison between experimental and theoretical guided modes. However, this model-based inverse approach tends to fail for the patients associated with poor guided mode information. A recent study has shown the potential of an automatic classification tool, Support Vector Machine, to analyze guided wave spectrum images independently of any waveguide model. The aim of this study is to explore how the classification accuracy varies with the number of features. Optimization was done using the Particle Swarm Optimization algorithm, while adjustment was made considering age, body mass index, and cortisone intake. The results show that adjusting the data and optimizing the parameters improved classification. Moreover, the number of features was reduced from 32 to 15, with 73.5% accuracy comparable to the gold standard.**

***Index Terms*—Ultrasonic guided waves, cortical bone, fracture classification, support vector machine, particle swarm optimization algorithm.**

I. Introduction

Osteoporosis is recognized as a skeletal disorder, caused by an imbalance in bone remodeling, which is influenced by the genetic code and several other factors, including the adequate level of physical, hormonal, and nutritional activity [1], [2]. Osteoporotic bone has increased porosity and decreased thickness that increases the risk of fracture. Worldwide, 1.6 million hip fractures occur annually and are expected to increase to 6.3 million by 2050 [3]. In addition, 1 in 3 women and 1 in 5 men over 50 years are expected to suffer from an osteoporotic fracture [2].

Currently, the *gold standard* for fracture risk assessment is dual-energy X-ray absorptiometry (DXA) [4], [5]. This technique generates a calibrated gray level image by applying a small dose of X-rays. This image provides bone mineral density by area as well as its normalized T-score counterpart. In fact, osteoporosis in adults is diagnosed on the basis of a T-score equal to or lower than -2.5. However, most people who suffer fragility fractures are above this limit [6], [7].

Within ultrasound techniques [8], another alternative is the bidirectional axial transmission device (BDAT) [9]. This device makes it possible to measure the propagation of guided waves, with a wavelength comparable to the cortical thickness [10]. One of the main results of the device is an guided wave spectrum image (GWSI) obtained with the SVD-based method applied to multiple transmitters and receivers [11]. With this image it is possible to implement an inverse problem providing porosity and cortical thickness values. However, this approach tends to fail for patients associated with poor guided mode information [12].

Recently, a parallel approach using machine learning has been proposed [13]. In this case, the structural and textural properties of the GWSI are studied without the need for any physical model. Machine learning is an area of Artificial Intelligence that, through computational methods, allows us to identify patterns and make predictions [14].

The support vector machine is one of the most popular machine learning algorithms, its objective is to find a hyperplane in an N-dimensional space that provides the best discrimination between two groups [15]. The hyperplane acts as the separating boundary, and can be linear or more complex such as Gaussian, polynomial, among others. Each dimension is called a feature and corresponds to a parameter of interest. In this study, these features come from clinical factors of the patient and the structural and textural analysis of the GWSIs. The problem arises that as the number of dimensions increases, the more complex it becomes to find a hyperplane that discriminates the groups. Several machine learning approaches have already been applied to osteroporosis, mainly for X-Ray modalities [16].

The objective of this study is to explore how the accuracy varies with the number of features sorted following their statistical significance, in order to search if a optimal combination of features exist. Finally, the results were compared with the gold standard DXA and the previous BDAT approach.

This document is organized as follows. Section II presents the materials and methods, Section III presents the results and finally, Section IV presents the conclusions and future work proposed for the study.

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II. Materials and Methods

A. Materials

We used the patient database of the BDAT pilot clinical study [17]. This is a cross-sectional or retrospective study, which means that two groups of patients are measured and their fracture history is taken into account. This study involved 211 patients, 110 without fracture and 104 with non-traumatic fracture. A total of 12.515 measurements were obtained with the 1 MHz BDAT device. Each measurement, as illustrated in Figure 1, is composed of two directions, Direction 1 corresponds to the distal wave propagation direction, i.e., from the elbow to the wrist, while the opposite proximal direction is denoted as direction 2. For both directions, GWSIs were obtained using the SVD method [11]. The GWSIs, denoted by $Norm(f,k)$, expressed in the frequency f - wavenumber domain k, can be interpreted as an enhanced spatiotemporal Fourier transform. The pixel value reflects on a scale from 0 to 1 the presence rate of the tested plane wave in the measured signals.

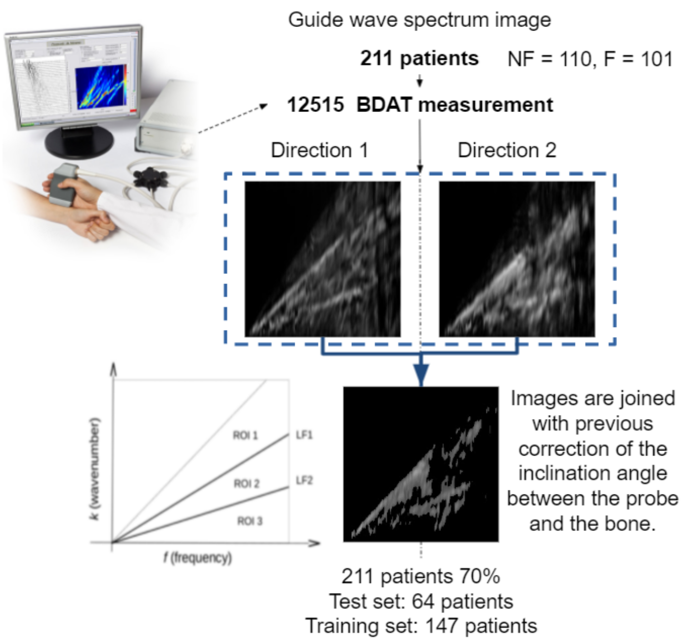

Fig. 1. Database construction: measurements are obtained on 211 patients with the BDAT device with two directions of propagation, the angle correction is then applied, finally the two images are merged and the noise is filtered.

B. Construction of the Support Vector

The same features of a previous study were considered [13]. The Support Vector contains 32 features: 4 from the structural similarity index measure (SSIM), 4 from the mean squared error (MSE) and 24 from the Grey Level Co-occurrence Matrices (GLCM) of three region of interest (ROI). First the features are considered alone or unadjusted. Then, the feature are adjusted using three clinical features, age, Body Mass Index (BMI) and used of glucocorticoids. Finally, the features were sorted considering their statistical significance obtained from the logistic regression analysis [13].

Finally, six random combinations of patients, with the same ratio of non fractured and fractured patients, were generated. These groups were used for training and testing.

C. Optimization algorithm

RBF Kernel SVM depends on two parameters γ and C, being real and positive. It is possible to optimize these parameters in order to improve the classification process. In this study, the *Particle Swarm Optimization* algorithm was used [18] to compute the best values of γ and C allowing to increase the accuracy. Similar works about parameter tuning of optimizer algorithms can be found in [19]–[21].

In our work, we previously define ranges for the two parameters γ and C, in order to suitably guide the search for the optimizer. Thus, γ takes vales from $[10^{-5}, 10^{+2}]$, and C varies in $[10^{-2}, 10^{+2}]$. The accuracy was optimized for each one of the 6 patient combinations and for each feature combination in order to extract the mean accuracy and the associated standard deviation. The optimized accuracy is then compared to the accuracy obtained on the 6 patient combinations using default parameters, $C = 1.0$ and $\gamma = 0.1$.

III. Results

Accuracy results in function of the feature number are shown in Figure 2, for default (left) and optimized with PSO (right) C and γ parameters.

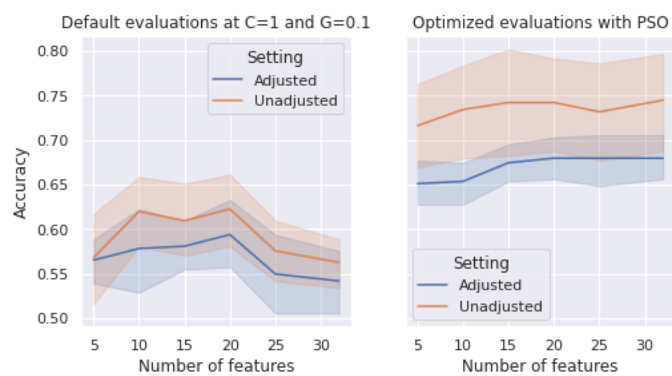

Fig. 2. Accuracy in function of feature number, considering default (left) or optimized (right) C and γ parameters of the RBF Kernel SVM for unadjusted and adjusted cases. Mean and standard deviations are obtained from the 6 patient combinations. Features are sorted with respect to their statistical significance,

Unadjusted and adjusted cases are considered. One can observed that in both cases, the accuracy increases with the age, BMI and cortisone intake adjustement. Likewise, accuracy also increases with optimization. In the default case, one can observe that accuracy presents a plateau for feature number ranging from 10 to 20, suggesting that an optimal feature combination exists. In the optimized case, the best accuracy is obtained for about 15 features. No significant accuracy improvement are observed with a larger feature number. The highest accuracy 73.5% [68.5 - 78.5] is comparable to the DXA performance 73% [66 - 79], obtained on the same patient database using logistic regression of the adjusted femoral neck

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bone mineral density [13]. However, it is worth to notice that the parameters γ and C differs for each evaluation.

IV. Conclusions

In this study, we considered a Support Vector including features obtained from textural and structural analysis of guided wave spectrum images as well as clinical factors, in order to classify two groups of patients, with or without non-traumatic fractures. This approach can be included in an affordable and portable device for osteoporosis evaluation such as the one developed by Azalée.

An advantage of this technique is that it does not require any physical models. The best accuracy is obtained using 20 adjusted features and optimized C and γ parameters. Optimization was done using the Particle Swarm Optimization algorithm, while adjustement was done considering age, body mass index and cortisone intake. The performance is comparable to the current gold standard DXA.

As future work, we propose to increase the number of patients in order to test other machine learning approaches. In particular, it is known that the effectiveness of deep learning increases with the size of the database [22]. In addition, we propose to study how these new approaches, from the point of knowing their interpretability [23], i.e. knowing how to explain the decisions and predictions of machines to justify their reliability.

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