

# Detecting Rheumatic Arthritis by Artificial Intelligent Multi-Parameter Classifications of Optical Tomographic Images

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**Abstract:** We demonstrate that sensitivity and specificity in detecting rheumatoid arthritis from optical tomographic images can be greatly increased when an artificial intelligent multi-parameter classifications method, called Self-Organizing Mapping (SOM), is used.

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## 1. Introduction

Sagittal laser optical tomography data (SLOT) has recently been employed to detect rheumatoid arthritis (RA) in finger joints [1]. This method relies on series of transillumination measurements, which are used as input to a model based image reconstruction code. The code produces cross sectional images of the absorption and scattering properties in the proximal interphalangeal (PIP) joints of the hands. Using data from 78 PIP joints, including data from patients diagnosed with RA as well as healthy volunteers, the authors investigated various single parameters such as minimum or maximum values of the absorption coefficient  $\mu_a$  and scattering coefficient  $\mu_s$  in an area of interest within a given image to determine what parameter provides the best distinction between affected and non-affected joints. Statistical analysis of the data revealed that, when using the minimum absorption coefficient  $\min(\mu_a)$ , sensitivity and specificity values of approximately 0.70 can be reached, while other parameters such as  $\max(\mu_a)$  or  $\min(\mu_s)$  yielded poorer classification results. In this study we explore if combining two or more parameters increases sensitivity and specificity. To test our hypothesis we used an extended data set of 178 images of PIP joints including the aforementioned data set.

## 2. Data

Measurements on the finger joints were performed with an optical scanning system [2,3]. The system is comprised of a single laser diode and single a silicon photo detector, which are scanned independently along a sagittal plane across the PIP joint. The transillumination data of multiple scans are input to a model-based iterative image reconstruction algorithms, which uses the equation of radiative transfer to model light propagation in tissue. The resulting SLOT images show the spatial distribution of two different optical properties,  $\mu_a$  and  $\mu_s$ . A region of interest (ROI) was defined within the SLOT images in order to extract different parameters for further analysis. Minimum-value  $\min(\cdot)$ , maximum-value  $\max(\cdot)$ , maximum-to-minimum-ratio and the statistical variance  $\text{var}(\cdot)$  of  $\mu_a$  and  $\mu_s$  values were drawn from the ROI in each of the 178 images.

## 3. Method

To analyze the data we implemented an artificial intelligent methodology commonly referred to as Self-Organizing Mapping (SOM). This approach allows to interpret (classify) more than one parameter simultaneously. Instead of determining the mean and standard deviation of just one parameter (e.g.,  $\min(\mu_a)$ ) for healthy and affected patient groups, and determining the significance of the difference between the two groups, the SOM approach allows to combine  $\min(\mu_a)$ ,  $\max(\mu_a)$ ,  $\min(\mu_s)$ , etc. in the analysis. Therefore, using SOM can transform feature vectors of arbitrary dimension into simplified generally 2-dimensional discrete maps (Kohonen layer) [4,5]. This type of neural network utilizes an unsupervised learning method, known as competitive learning in the field of neural information processing. It is useful for analyzing, in particular interpreting, complex data with a-priori unknown relationships or interdependencies [6], such as in case of the SLOT data.

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The finger joint data were analyzed (clustered) by SOM-networks of different Kohonen layer sizes. The outcomes were compared with benchmarks (gold standards) resulting from expert interpretations of magnet resonance images (MRI), ultrasound images (US), and clinical diagnosis (CL). This comparison can ensure to what extent the features (e.g., min, max) of the measured data ( $\mu_a$  and  $\mu_s$ ) can be described by class labels (“affected” and “non-affected”) of the given gold standards. Results of the discrimination can be visualized in the 2-dimensional Kohonen layer with neurons (groups) showing class labels based on a selection criterion as shown in Fig. 1C.

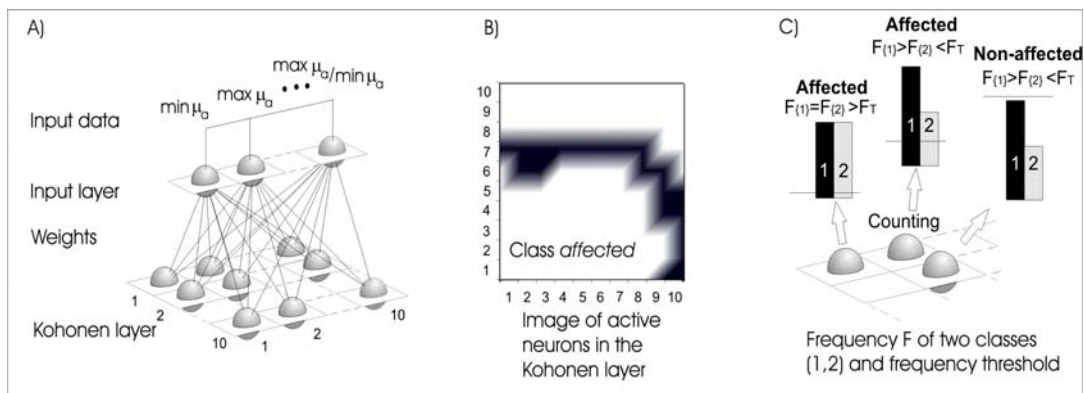


Fig. 1. Scheme for multi-parameter classifications based on SOM: A) Structure of a SOM neural network, B) Image of active neurons representing the class affected within the Kohonen layer after discrimination of the given input data, C) Frequency determination and final classification of the classes affected (black) and non-affected (gray) based on a variable frequency threshold  $F_T$ .

The frequency per class describes the number of identified finger joints. In other words, different multi-dimensional parameter spaces of  $\mu_a$  and  $\mu_s$ , which are separated by the SOM in to sub-groups (clusters), consist of clusters with varying number of “affected” and “non-affected” finger joints, although the physical optical data ( $\mu_a$  and  $\mu_s$ ) are similar. The above mentioned criteria determines units within the  $\mu_a$ - $\mu_s$ -spaces that represent a certain class very well or less good.

#### 4. Results and Discussion

The classification problem for detecting rheumatic arthritis in finger joints was conducted based on  $\mu_a$  and  $\mu_s$  values of the SLOT data by combining up to four different parameter (e.g.,  $\min(\mu_a)$ , the ratio  $\max(\mu_a)/\min(\mu_a)$  and  $\text{var}(\mu_a)$ ). Multi-dimensional input data were classified based on an SOM neural information processing approach. Moreover, the application of sensitivity-specificity-curves (ROC-curves) were used as a common way to model interpretation (classification) results with respect to the observer’s subjectivity (frequency threshold value). ROC-curves describe the sensitivity and the specificity of a classification result as functions of an expert's gold standard and frequency thresholds varying between 0 and 1 [7]. As above mentioned, a finger was classified as affected (or non-affected) when the frequency of this class for a certain neuron in the Kohonen layer of the SOM network was larger than the chosen threshold value and larger than the exclusive class non-affected (or affected). Thus, the neuron represents a group of data point with similar combined physical features, such as  $\{\min(\mu_a), \max(\mu_a)/\min(\mu_a), \text{var}(\mu_a)\}$ .

Different parameter combinations result in varying sensitivities and specificities for each benchmark (gold standard) as result of changing frequency thresholds as well as dimension of the  $\mu_a$ - $\mu_s$ -parameter spaces and size of the Kohonen layers (Fig. 2). Some classifications can lead to higher sensitivities, whereas others to higher specificities. For each benchmark, we calculated the sensitivity (SE) and specificity (SP) for the point on the ROC-curve with the highest Youden index (Y) [8], which characterized the point on the curve closes to sensitivity=specificity=1. The best results are based on the 3-d feature space  $\{\min(\mu_a), \max(\mu_a)/\min(\mu_a), \text{var}(\mu_a)\}$ . If MRI, which is widely accepted in the clinical field as gold standard for RA diagnostic, is used as benchmark we find  $SE=1$ ,  $SP=0.87$ , and  $Y=0.13$ . These are excellent values that put SLOT technology clearly in the range of clinically useful diagnostic methods. The same SE, SP, and Y values are found when CL is used as benchmark, while using US as gold standard yields,  $SE=1.00$ ,  $SP=0.88$ , and  $Y=0.12$ .

Results also show that the classification quality is uncorrelated to the dimensionality of the parameter space. Thus, many combined parameters do not necessarily determine a high separability of affected and non-affected fingers. Ideally, parameters should be chosen based on their physical relevance (e.g., non-affected fingers show high  $\text{var}(\mu_a)$ -values). Such information, which was a-priori not available, could be determined based on the SOM approach.

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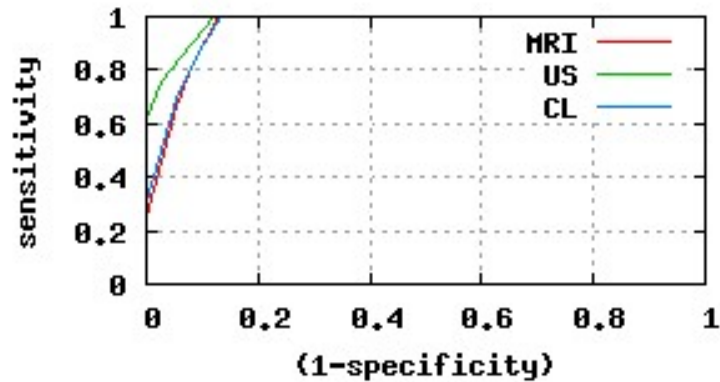


Fig. 2. ROC-curves describe the quality of an interpretation of  $\{\min(\mu_a), \max(\mu_a)/\min(\mu_a), \text{var}(\mu_a)\}$  for each benchmark. Best results are based on a 7x7 SOM and data set.

Specificity and sensitivity are also uncorrelated to the size of the Kohonen layer that determines the precision of an classification. A Kohonen layer of 3 by 3 neurons can represent approximately 1/10 of 100 data points in a given data set. Each of the resulting 9 clusters contains similar data points (from a physical view point), whereas their class labels might be dissimilar (low specificity or sensitivity) or similar (high specificity or sensitivity) according to a given benchmark and frequency threshold. A 5 by 5 Kohonen layer separates the 100 data points with a 250% higher precision than the 3x3 SOM. Hence, each neuron represents a smaller set of physical similar data points. Thus, the number of class members and the class frequency of this cluster (neuron) changes as well as sensitivity and specificity values. For example, a neuron of the 3x3 SOM represents a cluster of 15 data points with 8 affected fingers (53%) and 7 non-affected fingers (47%). On the other hand, the neuron of the 5x5 SOM represents this cluster that is now consisting of 10 data points with 3 affected fingers (30%) and 7 non-affected fingers (70%). The other 5 data points may now belong to other clusters. Finally, these class frequency changes can alter the resulting ROC-curves significantly.

## 5. Conclusion

The identification of rheumatoid arthritis in finger joints is possible by analyzing sagittal laser optical tomography images when compared to other imaging techniques. Up to four parameters in combination of the absorption  $\mu_a$  and scattering coefficient  $\mu_s$  were considered as part of this study. Multi-dimensional parameter spaces were analyzed by an artificial intelligent interpretation approach, called Self-Organizing Mapping (SOM).

Results of this study suggest that sensitivities and specificities of the multi-parameter image classifications are uncorrelated to the dimensionality of the parameter spaces. Combinations of more than 3 parameters between the absorption and scattering coefficient, for instance, can lead to very smaller sensitivities and specificities. However, proper parameter combination  $\{\min(\mu_a), \max(\mu_a)/\min(\mu_a), \text{var}(\mu_a)\}$  can be determined that result into higher sensitivities and specificities when compared to single-parameter classifications and different expert interpretations of magnet resonance images (MRI), ultrasound images (US), clinical diagnosis (CL) and optical images (SLOT). Using MRI as clinical gold standard we find that sensitivity and specificity values up to 0.87 and 1 respectively can be achieved. This makes SLOT imaging a competitive diagnostic tool for the detection of RA in finger joints.

## 6. References

- [1] Scheel A.K. Backhaus M. Klose A. D. Moa-Anderson B. Netz U.J. Hermann K-G.A., Beuthan J. Müller G.A. Burmester G.R. Hielscher A.H. "First clinical evaluation of sagittal laser optical tomography for detection of synovitis in arthritic finger joints," *Ann Rheum Dis* **64**, 239-245 (2005).
- [2] Klose A.D. Hielscher A.H. Hanson K.M. Beuthan J. "Two and three-dimensional optical tomography of a finger joint model for diagnostic of rheumatoid arthritis," *Proc SPIE Int Soc Opt Eng* **3566**, 151-60 (1998)
- [3] Hielscher A.H, Klose A.D. Scheel A. Moa-Anderson B. Backhaus M. Netz U. Beuthan J. "Sagittal Laser Optical Tomography for Imaging of Rheumatoid Finger Joints," *Physics in Medicine and Biology* **49**(7), 1147 - 1163 (2004).
- [4] Kohonen T. "Self-organizing formation of topologically correct feature maps," *Biol. Cyb.* **43**(1), 59-69 (1982).
- [5] Kohonen T. "Self-Organizing Maps" 3rd edition, Springer, Berlin (2001).
- [6] Klose C.D. "Self-Organising Maps for Geoscientific Data Analysis: Geological Interpretation of Multi-dimensional Geophysical Data," *Computational Geosciences*, **10**(3), 265-277 (2006).
- [7] Metz C.E. Pan X.C. "Proper binormal ROC curves: Theory and maximum likelihood estimation," *Journal of Mathematical Psychology* **43**,1-33 (1999).
- [8] Youden WJ. "Index rating for diagnostic tests," *Cancer* **3**, 32-5 (1950).