Applied Soft Computing 44 (2016) 89–100

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Intravascular ultrasound-based tissue characterization using modular network self-organizing map

Kazuhiro Tokunaga [a,*], Eiji Uchino [b,c], Hiroki Tanaka [b], Noriaki Suetake [b]

[a] Department of Ocean Mechanical Engineering, National Fisheries University, 2-7-1 Nagata-Honmachi, Shimonoseki 759-6595, Japan
[b] Graduate School of Science and Engineering, Yamaguchi University, 1677-1 yoshida, yamaguchi-shi 753-8511, Japan
[c] Fuzzy Logic Systems Institute, 680-41 Kawazu, Iizuka 820-0067, Japan

ARTICLE INFO

Article history:
Received 21 July 2015
Received in revised form 2 February 2016
Accepted 18 March 2016
Available online 6 April 2016

Keywords:
Intravascular ultrasound
Tissue characterization
Modular network self-organizing map
Self-organizing map

ABSTRACT

The intravascular ultrasound-based tissue characterization of coronary plaque is important for the early diagnosis of acute coronary syndromes. The conventional tissue characterization techniques however cannot obtain sufficient identification accuracy for various tissue properties, because the feature employed for characterization are static features, which lack dynamical information about backscattered radio-frequency (RF) signals.

In this work, we propose a new intravascular ultrasound-based tissue characterization method that uses a modular network self-organizing map (mnSOM) in which each module is composed of an autoregressive model for representing the dynamics of the RF signals.

The proposed method can create a map of various dynamical features from the RF signal. This map enables generalized tissue characterizations. The proposed method is verified by comparing its tissue characterization performance with that of the conventional method using real intravascular ultrasound signals.

1. Introduction

Acute coronary syndromes (ACS) are caused by the rupture of vulnerable atherosclerotic plaques [1]. Friedrich et al. reported that the risk of plaque rupture depends on the histological pattern, i.e., the histological composition related to the stability of the atherosclerotic plaques [2]. Thus, it is important to identify whether the histological compositions have an unstable pattern (vulnerable atheroma) before the plaque ruptures. Therefore, tissue characterization of atherosclerotic plaques is an important requirement in clinical practice.

One method of examining the histological composition within the vessel wall is to use backscattered intravascular ultrasound (IVUS) [3,4]. IVUS provides a tomographic visualization of the coronary artery and a real-time in vivo image of the plaque. For these reasons, the IVUS method has been employed for the analysis of ACS [5–8].

In previous studies, several analysis techniques have been proposed for conventional tissue characterization using IVUS. One such method is integrated backscatter (IB) analysis [9,10]. In IB analysis, tissues are classified according to their IB value, which is the locally averaged power of backscattered ultrasound. IB analysis is effective in a limited number of cases. The IB values do not, however, always represent the characterization of the tissues, because IB values are substantially affected by the intensity of the backscattered ultrasound. The intensity of the ultrasound depends on the distance between the plaque and the probe, meaning it is difficult to classify plaque tissues using only the IB values.

To address this problem, spectral analysis methods have been proposed that use a backscattered IVUS radio-frequency (RF) signal in the frequency domain. In studies by Moore et al. and Nair et al. [11,12], pixels in the IVUS image were classified according to a feature vector formed from the Fourier spectrum of the local RF signal. Additionally, a k-nearest neighbor (kNN) method has been employed to classify the tissues [13,14]. In those works, a prototype vector represents the Fourier spectrum of the local RF signal. It has been reported that kNN can classify tissues flexibly and robustly without any pre-processing of the training feature vectors. However, kNN cannot perform a satisfactory classification if the distribution of the feature vectors overlap. A large degree of overlap among the feature vectors occurs in the feature space, as the composition of the tissues has infinite variety. Therefore, the generalization performance decreases. In addition, static feature vectors, which lack dynamical information about the RF signal, are

* Corresponding author.
E-mail addresses: tokunaga@fish-u.ac.jp (K. Tokunaga), uchino@yamaguchi-u.ac.jp (E. Uchino), s015vc@yamaguchi-u.ac.jp (H. Tanaka), suetake@sci.yamaguchi-u.ac.jp (N. Suetake).

http://dx.doi.org/10.1016/j.asoc.2016.03.017
1568-4946/

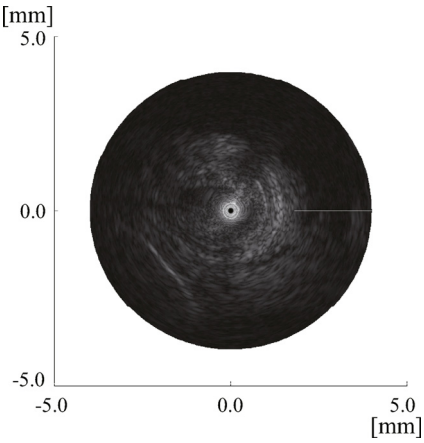

Fig. 1. B-mode image of a blood vessel cross-section.

used to identify the tissue types. The addition of dynamic information to the tissue characterization should serve to improve the identification accuracy, as the ultrasonic echo in tissues changes dynamically according to various factors.

In this paper, to realize the precise tissue characterization of coronary plaques, we propose a new method using a modular network self-organizing map (mnSOM) [15] in which each module is composed of an autoregressive (AR) model. We call the proposed method "AR-mnSOM."

The mnSOM is a modular network in which every reference vector unit of Kohonen's self-organizing map (SOM) [16] is replaced by a trainable functional module such as a neural network. Moreover, a competitive and cooperative algorithm of the SOM has been introduced to the learning algorithm of the modular network. The mnSOM is able to perform higher-order information processing. For example, Minatohara et al. have proposed an adaptive controller that uses an mnSOM in which each module is composed of a linear dynamic prediction model and a controller model [17]. In this method, the stability of both learning and control is better than that in the adaptive controllers of conventional modular networks.

In this work, we employ an AR model for the mnSOM module. The AR model, which is a linear prediction model, can represent simple dynamical models. Moreover, the neighboring AR modules in the mnSOM map apply competitive and cooperative learning to represent similar dynamics. For this mechanism, AR-mnSOM creates a map of a simple dynamical model. In addition, the interpolation functions produced by the cooperative algorithm give the AR-mnSOM strong generalization ability. The map given by the AR-mnSOM can then be used to make highly generalized tissue characterizations.

In this paper, the proposed method is applied to the tissue characterization problem using real IVUS data, and its performance is verified quantitatively and qualitatively. The validity and practical effectiveness of the proposed method for tissue characterization are confirmed by the experimental results.

2. Intravascular ultrasound

IVUS is used for tissue characterization in the vessel wall. In particular, the ultrasound signal (commonly referred to as the RF signal) is obtained from a probe mounted on a catheter that is inserted into a coronary artery. The strength of the RF signal differs according to depth or tissue characterization.

The RF signals are obtained at all circumferences of the intravascular region, as the ultrasound is transmitted and received while rotating the probe. The strength of the RF signal at all circumferences is displayed as a B-mode image, as shown in Fig. 1. That is, Fig. 1 represents the blood vessel cross-section. Moreover, the probe is moved backward in the blood vessel while it is rotated. Thus, the sets of RF signals in each vascular cross-section are obtained at intervals of, e.g., 5 μm.

3. AR-mnSOM

An AR-mnSOM is an mnSOM in which a unit module is composed of an AR model (see Fig. 2).

The mnSOM, proposed by Tokunaga and Furukawa [15], has a network architecture in which each unit module is composed of a neural network, and those networks are arranged in a lattice. In other words, each vector unit in Kohonen's SOM is replaced by a neural network module. A learning algorithm including competitive and cooperative mechanisms is introduced to the modular network. The mnSOM, thus, creates a map of functions (input–output models), as the neighborhood modules represent similar functions (input–output models). Moreover, the composition of the unit modules can be changed according to the task [18–22]. These features have led to mnSOMs being applied to high-dimensional pattern classification and recognition in time-series data [23,24].

In the proposed AR-mnSOM, the unit module of the mnSOM consists of an AR model, which is a typical prediction method for time-series data (Fig. 2). The AR model is a linear dynamical model that predicts the future values of time-series data. Consequently, the AR-mnSOM generates a map of the prediction models based on the similarity of their dynamics. Here, it is also possible to employ an autoregressive moving average (ARMA) model, a recurrent neural network (RNN) or a radial basis function (RBF), instead of the AR model. The AR model, however, is used to mnSOMs module in this work. The main reason for using the AR model is that the AR model is suitable for the theory and the algorithms of the mnSOM compared with other models. Moreover, reliability and effectivity of using the AR model has been verified in previous work [17]. Besides, it is difficult to analyze the map of the mnSOM composed of the neural networks that represent the non-linear dynamics. For problems in the case of learning the non-linear dynamics using multiple modules are discussed in reference [25]. We need to analyze the inner representation of each module and the contexture of the whole map because one aims of the present work is to verify the effectiveness of dynamical features in the tissue characterization of the IVUS. Therefore, we employ the AR-mnSOM in which the theory, the algorithm and way of analysis have been established.

In this study, short time signals (called episodes in this paper) are separated from the RF signals, and applied to the AR-mnSOM as input (see Fig. 3). The model parameters in each AR module are updated using the method of steepest descent, incorporating the competitive and cooperative mechanisms of the mnSOM. As a result, each AR module in the mnSOM represents a different dynamical model. After the learning process, it is possible to form a classification based on the tissue characterization given by the AR-mnSOM, because the dynamical properties of the RF signal depend on the tissue characterization.

3.1. Theory of AR model

In the AR model, signal $x(t)$ at time t is defined as follows:

$$x(t) = \sum_{i=1}^{M} w_i x(t-i) + \sigma_t, \tag{1}$$

where $w_i (i = 1, \ldots, M)$ is an autoregression coefficient, M is an order, and σ_t is a white noise. Eq. (1) gives a prediction of $x(t)$ from