EMPIRICAL MODE DECOMPOSITION BASED SUPPORT VECTOR MACHINES FOR MICROEMBOLI CLASSIFICATION

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ABSTRACT
The classification of circulating microemboli, in the bloodstream, as gaseous or particulate matter is vital for selecting appropriate treatment for patients. Until now, Doppler techniques have shown some limitations to determine clearly the nature of circulating microemboli. The traditional techniques are largely based on the Fourier analysis. In this paper we present new emboli detection method based on Empirical mode decomposition and support vector machine using Radio Frequency (RF) signal instead of Doppler signals.

1. INTRODUCTION
An embolus can take the form of solid matter or air, it is a foreign body that travels in the bloodstream. The creation of the embolus in the human body depends on different physiological, physical, and intervention mechanisms [1], it can travel to any part of the body, accounting for many serious (and sometimes life-threatening) disorders thus the importance of an automatic classification system. Unfortunately, Doppler processing, which is commonly used for emboli detection, presents some limitations to distinguish between embolus and artefacts [2,3].

Recent approaches based on the analysis of radio frequency (RF) signals was investigated to classify microemboli [4,5]. These techniques exploit the nonlinear behavior of gaseous bubbles. The aim of this study is the analysis of RF signals using Empirical mode decomposition and support vector machine in order to classify emboli.

Since its first appearance in the nineties, the Empirical Mode Decomposition (EMD) is raising great attention [6]. Indeed, it received wide interest in a variety of fields such as biomedical engineering [7,8], space research [9], hydrology [10], synthetic aperture radar [11], speech enhancement [12], water marking [13], etc. The EMD technique decomposes signals into Intrinsic Mode Functions (IMFs) which are a series of zero mean oscillatory functions. Each IMF is iteratively extracted using a sifting process, applied to the residual multicomponent signal. One sifting iteration involves: (i) calculate the local mean of the residual signal, (ii) subtract it from the residue. This process is repeated until it converges to a designated IMF. The local mean is calculated as the half sum of the upper and the lower envelopes, achieved by interpolating between local minima and maxima, respectively, using cubic splines [6].

Support Vector Machine (SVM) is a promising pattern classification technique suggested by Vapnik and co-workers [14-16]. Unlike traditional techniques which reduce the empirical training error, SVM minimizes an upper bound of the generalization error through maximizing the boundary between the separating hyperplane and the data. SVMs have been used in a wide range of real world problems such as text categorization [17], hand-written digit recognition [18], tone recognition [19], image classification and object detection [20], cancer diagnosis [21], microarray gene expression data analysis [22]. It has been revealed that SVM is consistently superior to other supervised learning methods [23].

In this study experimental results are obtained for two different concentrations of microbubbles and for two different Mechanical Index (MI).

The rest of this manuscript is organized in four sections. Section 2 and 3 describe the basics of empirical mode decomposition and support vector machines when used as classifier. Section 4 presents the material and methods used in this experimental study. In Section 5 we discuss the experimental results obtained for two concentrations (5 μl and 10 μl) of microbubbles at low (0.2) and high (0.6) MI (the mechanical index). Section 6 draws the conclusion of this study.

Figure 1 shows the general bloc diagram of the SVM classification model used in our study, the input signal is first detected and collected (signal acquisition). Then a certain feature set is extracted from the collected signal using the EMD method. This feature is used as an input to the SVM model which provides in its output a value of 1 or -1 for gaseous or solid emboli respectively.
2. EMPIRICAL MODE DECOMPOSITION

EMD, proposed by Huang et al [6], is a method to decompose nonstationary and non-linear time series into diverse monotonic components named as intrinsic mode functions (IMF) of different time scales. The most appealing nature of EMD is its dependency on the data-driven mechanism which does not need a priori known basis unlike Fourier transform and Wavelet.

The EMD method identifies all the local maxima and minima for an input signal \( x(t) \) which are related by spline curves to form the upper and the lower envelopes, \( e_{up}(t) \) and \( e_{low}(t) \), respectively. The mean of the two envelopes is given by \( m(t) = \frac{e_{up}(t) + e_{low}(t)}{2} \) and is subtracted from the signal using \( q(t) = x(t) - m(t) \).

An IMF \( c_i(t) \) is obtained if \( q(t) \) satisfies the two conditions of IMF, these are, the number of extrema and number of zero crossings is either equal or differs at most by one, and the envelopes defined by the local maxima and minima are symmetric with respect to zero mean. This procedure is called as the sifting process. Then \( x(t) \) is replaced with the residual \( r(t) = x(t) - q(t) \). If \( q(t) \) is not an IMF, \( x(t) \) is replaced with \( q(t) \). The above process is repeated until the residual satisfies the stopping criterion called sum of difference, \( S_D \) shown in equation (1), which is generally set between 0.2 and 0.3.

\[
S_D = \sum_{k=0}^{T} \left| q_{k-1}(t) - q_k(t) \right|^2 / q_{k-1}(t).
\]  

(1)

At the end of this process the signal \( x(t) \) would result in \( N \) IMFs and a residue signal as in equation (2).

\[
x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t)
\]

(2)

Where \( n \) represents the order of IMFs, \( n = 1 \) to \( N \) and \( r_N \) denotes the final residue which can also be considered as an IMF, shown in equation (3).

\[
x_d(t) = \sum_{i=1}^{N} c_i(t)
\]

(3)

Here, \( N_i \) is the total number of IMFs including the residue. The signal \( x(t) \) is decomposed such that the lower-order components represent fast oscillation modes and higher-order components represent slow oscillation modes. A detailed explanation of the method is provided in [24].

3. SUPPORT VECTOR MACHINE

The Support Vector Machine (SVM) [14-16] is a novel machine learning technique based on a statistical learning theory proposed by the Vapnik group in 1995. It has gained increasing attention in areas that range from pattern recognition to regression estimation, due to its perfect learning performance. Based on the structural risk minimization principle [25], it can perfectly improve the generalization ability of a learning machine. At the same time, an optimization problem can be transformed into a convex quadratic programming problem. The solution of a quadratic programming problem is the unique optimization solution of the whole. Hence, SVM does not have the problems with local extrema that are present for traditional neural networks, which require large numbers of training samples.

The SVM performs pattern recognition for two-classes problems by determining the hyperplane of separation with the maximum distance to the narrowest points of the positioning of formation. These points are called the vectors of support.

Given a training sample set, \( W = \{ (x_i, y_i), i = 1 \ldots l \} \), an input sample, \( x_i \in \mathbb{R}^d \), and class labels, \( y_i \in \{-1, 1\} \); for a linearly separable binary classification problem, the separation hyperplane is:

\[
x \cdot w + b = 0.
\]

(4)

Where \( w \) is a weight vector and \( b \) is a bias.

The optimal hyperplane that separates the data into two classes minimizes:

\[
\phi(w) = \frac{1}{2} \| w \|^2 = \frac{1}{2} (w \cdot w).
\]

(5)

Subject to the constraint:

\[
y_i (x_i \cdot w + b) \geq 1.
\]

(6)

In many practical situations, a separating hyperplane does not exist. To allow for the possibilities of violating the constraint equation (6), slack variables, \( \xi_i > 0 \), are used to get:

\[
y_i (x_i \cdot w + b) \geq 1 - \xi_i, i = 1,\ldots,l.
\]

(7)

The optimization problem now becomes:

\[
\phi(w, \xi) = \frac{1}{2} (w \cdot w) + \sum_{i=1}^{l} \xi_i, i = 1,\ldots,l.
\]

(8)
Where \( c \) is a user-defined constant, called a trade-off factor, which determines the balance between the maximization of the margin and the minimization of the classification error. Introducing Lagrange multipliers \( \alpha_i \) and using the Karush–Kuhn–Tucker theorem of optimization gives the solution as follows:

\[
w = \sum_{i=1}^{l} \alpha_i y_i x_i .
\]

(9)

Only a few of the \( \alpha_i \) coefficients are nonzero. The corresponding \( x_i \) values are known as support vectors, and they also define the decision boundary. At the same time, all other training samples with zero \( \alpha_i \) values are now rendered irrelevant. Finally, the decision function can be obtained as follows [25]:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{l} y_i \alpha_i (x_i, x) + b \right).
\]

(10)

SVM was originally designed for linear binary classification. In practice, many applications of SVM are nonlinear classification problems. For nonlinear classification problems, we can use nonlinear transforms. A transformation, \( \Phi(x) \), maps the data from the input space to a feature space that allows linear separation. We then seek the optimization separation plane in feature space. One only needs an inner product operation in feature space. The inner product operation may be implemented by a certain function (called a kernel function). In SVM, we introduce a kernel function \( K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j) \) to perform the transformation. Then the basic form of SVM can be obtained [26]:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{l} \alpha_i y_i K(x_i, x_j) + b \right).
\]

(11)

The commonly used kernel functions are presented in Table 1 [27].

<table>
<thead>
<tr>
<th>Kernel function type</th>
<th>Expressions</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear (linear)</td>
<td>( K(x_i, x_j) = x_i \cdot x_j )</td>
<td></td>
</tr>
<tr>
<td>Polynomial (poly)</td>
<td>( K(x_i, x_j) = \left(x_i \cdot x_j + 1\right)^q )</td>
<td>degree of polynomial kernel</td>
</tr>
<tr>
<td>Radial basis (rbf)</td>
<td>( K(x_i, x_j) = \exp\left[-\frac{|x_i - x_j|^2}{2\alpha^2}\right] )</td>
<td>width of radial basis kernel</td>
</tr>
</tbody>
</table>

In our case, radial basis kernel was used to differentiate between gaseous and solid embolus, grid search is used to optimize the parameters of the RBF kernel.

More details about recent developments of SVM can be found in [28].

## 4. EXPERIMENTAL SET-UP

The experimental set-up consists of a nonrecirculating flow phantom containing a 0.8mm diameter vessel, see figure 2. A continuous flow carries the Sonovue microbubbles through the insonified vessel. The concentration of contrast agent microbubbles is chosen to obtain comparable fundamental scattering amplitude than non perfused tissue used to simulate the response of a solid embolus.

![Figure 2. Experimental set-up](image)

The ultrasound waves were generated by a VF13-5 probe connected to a Siemens Antares scanner. The acquisitions were performed at 1.82MHz transmitting frequency in Tissue Harmonic Imaging (THI) mode. Two concentrations of the contrast agent were used, 5μl and 10μl. The microbubbles were administered into a 200 ml volume of Isoton [4].

Figure 3 shows the positions where RF signals corresponding to a solid embolus and gaseous embolus are extracted.

![Figure 3. Examples of grey scale images acquired: A. MI= 0.2, B. MI= 0.6 for two microbubbles concentrations](image)
Figure 4. Examples of RF signals A. MI= 0.2, B. MI= 0.6.

Figure 4 displays two examples of RF signals extracted from the obtained experimental grayscale images. Panel A presents a RF signal backscattered by a solid and a gaseous embolus at low MI (0.2). We note that the acoustic pressure is not sufficient to start nonlinear microbubbles oscillations. Panel B displays the RF signal of each type of embolus at a higher MI (0.6) in this case; the propagation of an ultrasound wave becomes nonlinear, thus a nonlinear behavior of both gaseous and solid particles is observed [4].

The number of IMFs generated varies with the length of signal, since longer signals contain longer timescale components, and hence more IMFs. An example of some of the IMFs produced from one RF signal is given in Figure 5.

Figure 5. Decomposition results via EMD method.

In theory EMD can separate different physical components. However, in practice the approach does not guarantee to extract the information exactly as required. For the RF signals here, there is not a perfect separation of gaseous embolus and solid embolus into the different IMFs. Although this means that microemboli cannot be reliably detected using only one IMF alone, a selection can be used to provide a robust detection method.

Here, we calculate the energy for each IMF and residue, we obtain $E_1, E_2, E_3, E_4$ and $E_r$. These characteristics are used as input to the SVM classifier. Where $E_i$ is the IMF$_i$ energy, and $E_r$ is the residue energy. The energy, E, of the IMF and the residue is established by:

$$E = \int_0^{t_0} |IMF|^2 \, dt. \quad (12)$$

Where $t_0$ is the signal duration.

5. RESULTS AND DISCUSSION

Table 1 and 2 summarize the percentage of correct classification of microemboli using the SVM as a function of the input parameters and the mechanical index respectively for two concentrations of microbubbles (5μl and 10μl).

Table 2. Correct classification rate of gaseous and solid emboli with two concentrations of microbubbles (5μl and 10μl) at low MI (0.2) and high MI (0.6).

<table>
<thead>
<tr>
<th>Results with C</th>
<th>C=5μl Low MI</th>
<th>C=5μl High MI</th>
<th>C=10μl Low MI</th>
<th>C=10μl High MI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaseous Emboli</td>
<td>100%</td>
<td>91.67%</td>
<td>100%</td>
<td>91.67%</td>
</tr>
<tr>
<td>Solid Emboli</td>
<td>83.33%</td>
<td>83.33%</td>
<td>83.33%</td>
<td>91.67%</td>
</tr>
<tr>
<td>Average rate</td>
<td>91.67%</td>
<td>87.50%</td>
<td>91.67%</td>
<td>91.67%</td>
</tr>
</tbody>
</table>

Figure 6. Correct classification rate of gaseous and solid emboli with two concentrations of microbubbles (5μl and 10μl) at low MI (0.2) and high MI (0.6).

The results show that for the concentrations of microbubbles 5μl at low MI and 10μl at low and high MI, the SVM classification model used in this experiment reaches a correct classification rate of 91.67%, but for the concentration of microbubbles 5μl at high MI; the correct classification rate is 85.50%.
6. CONCLUSION

The EMD offers a method by which RF signals from the experiment can be analyzed for the classification of the microemboli within the flow phantom. EMD is used to decompose the signal into a series of components, termed IMF. The method offers the ability to provide an automatic classification system; it has demonstrated that the use of radio frequency signal processing could offer better classification of microemboli as solid or particulate matter than the commonly used Doppler processing.

Using the empirical mode decomposition and the support vector machines as a classifier and the energy of the IMFs as inputs parameters allows the classification of embolus with a sensitivity of 91.67%.

The technique still needs a clinical trial and verification to demonstrate the additional benefit.

The main message of this study is to validate this strategy in a simple and a controlled experimental environment before further pre-clinical and clinical validations are undertaken.

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