33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

ε-Tube Regression: A New Method for Motion Artifact Reduction

Sardar Ansari, Kevin Ward and Kayvan Najarian

Abstract— **This paper introduces a new regression method, called ε-tube regression (ε-TR), for motion artifact reduction in physiological signals. It forms a tube arround the data which leads to an approximation that models only the motion artifact and not the target signal. Moreover, ε-TR prescribes the shape of the approximation using the available information about the motion artifact. The results show that ε-TR can effectively remove the motion artifacts from the impedance signal measured on the arms.**

I. INTRODUCTION

Support Vector Machine (SVM) [1] is one of the most recent and successful algorithms in machine learning. It has been extensively used in many different applications. The regression version of the SVM algorithm, Support Vector Regression (SVR), is the focus of this paper. The basic idea behind SVR is to build a regression model that minimizes the empirical risk calculated using the Vapnik's ε-intensity linear loss function. This way, SVR algorithm forms a tube, with size ε, around the function. The approximation error is zero at any given point if the approximated value is inside the tube at that point. Otherwise, the error is equal to the distance between the approximation and the tube.

There are many medical applications whose aim is to monitor some physiological signal. However, the target signal is often distorted by motion artifact. In particular, removing the motion artifact is a crucial task in the portable monitoring of the physiological signals. Therefore, robust and effective motion artifact reduction methods are required to deal with the motion artifact reduction problem. Many of the physiological signals are periodic signals with constant amplitudes or amplitude that changes slowly. When measured during motion, these signals are often combined with motion artifacts whose amplitude is bigger than the target signal. The idea of the ε-tube can be used to solve the problem of the motion artifact since it can model the motion artifact which appears as changes with large amplitudes, and avoids modeling the target signal which will eventually lie within the tube. The approximated motion artifact can then be subtracted from the original signal to recover the target signal. An example of a physiological signals that is susceptible to motion artifact is impedance signal. Impedance signal can be used to extract the respiratory rate [2] which is a valuable physiological signal. The proposed method in this paper, ε-tube regression (ε-TR), is used to reduce the motion artifact in the impedance signal that is measured on the subject's arms.

This material is based upon work supported by the National Science Foundation under Grant No.IIS0758410.

S. Ansari is with the Department of Computer Science, Virginia Commonwealth University, Richmond, VA, USA ansaris2@mymail.vcu.edu

Kevin Ward is with the Department of Emergency Medicine, Virginia Commonwealth University, Richmond, VA, USA krward@vcu.edu

K. Najarian is with the Department of Computer Science, Virginia Commonwealth University, Richmond, VA, USA knajarian@vcu.edu

The non-linear version of the SVR uses the idea of transforming the data into a feature space using kernel functions. This way, one activation function (AF) is placed at every data point, and the SVR algorithm selects the appropriate ones (support vectors) to build the model and calculates the weights of the selected AFs. As a result, any function can be approximated using the SVR algorithm. This makes SVR a universal estimation algorithm which can be used to estimate any function in any application. The drawback is that the user does not have enough control over the process of support vector (SV) selection, and the existing knowledge about the system cannot be infused into the model. For example, in motion artifact reduction, the overall shape of the artifact is often known (it can be measured using an accelerometer sensor), and this shape can be used to prescribe the final structure of the estimation. However, this information can not be used in the SVR algorithm to prevent SVR from choosing wrong SVs in modeling the motion artifact.

The aim of this paper is to provide a new estimation method that uses the idea of the ε-tube but prevents the problem of SV selection described above. The shape of the approximation function is fixed prior to the learning phase in this method, and only the parameters of the prescribed shape are subject to learning.

A. Support Vector Regression

The goal of any linear estimation algorithm is to find the best model parameters, $\mathbf{w}$ and b, such that the error between the estimation $f(\mathbf{x},\mathbf{w}) = \mathbf{w}^T\mathbf{x} + b$ and the target values y_i for the data points $\{\mathbf{x}_i, y_i\}$ is minimized regarding an objective function. The risk function associated with SVR encompasses two terms,

$$R = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}|y_i - f(\mathbf{x}_i,\mathbf{w})|_\varepsilon. \quad (1)$$

The first term ensures the smoothness and the generalization capability of the model while the second one minimizes the error and the number of data points that lie outside the tube. The parameter C controls the balance between the two, and the Vapnik lose function $|y_i - f(\mathbf{x}_i,\mathbf{w})|_\varepsilon$ is defined as

$$|y_i - f(\mathbf{x}_i,\mathbf{w})|_\varepsilon = \max(0, |y_i - f(\mathbf{x}_i,\mathbf{w})| - \varepsilon). \quad (2)$$

Using the definition of the Vapnik's loss function, one can

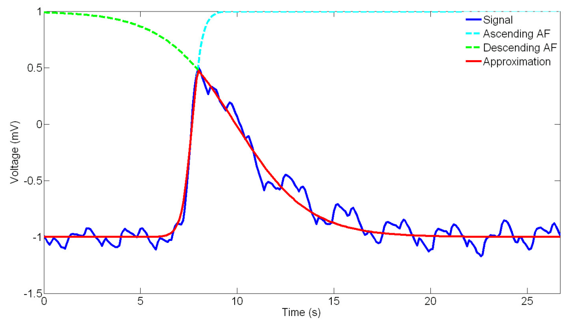

Fig. 1. Approximating the motion artifact with two tangent sigmoid AFs

define the slack variables ζ and ζ^* as follows.

$$\begin{aligned} &|y_i - f(\mathbf{x}_i, \mathbf{w})| - \varepsilon = \zeta \text{ for data 'above' the tube, and} \\ &|y_i - f(\mathbf{x}_i, \mathbf{w})| - \varepsilon = \zeta^* \text{ for data 'below' the tube} \end{aligned} \tag{3}$$

Therefor, minimization of the risk function R equals the minimization of the risk

$$R_{\mathbf{w},\zeta,\zeta^*} = \frac{1}{2}\|\mathbf{w}\|^2 + C\left(\sum_{i=1}^{n} \zeta_i + \sum_{i=1}^{n} \zeta_i^*\right) \tag{4}$$

subject to the constraints

$$y_i - \mathbf{w}^T \mathbf{x}_i - b \leq \varepsilon + \zeta_i, \quad i = 1..n \tag{5}$$

$$\mathbf{w}^T \mathbf{x}_i + b - y_i \leq \varepsilon + \zeta_i^*, \quad i = 1..n \tag{6}$$

$$\zeta_i \geq 0, \quad \zeta_i^* \geq 0, \quad i = 1..n \tag{7}$$

Forming the dual Lagrangian of the above optimization problem will lead to a standard quadratic optimization problem in terms of the dual Lagrangian multipliers and the input data. However, the dual problem is not the subject of this paper and is not discussed here. One can build a non-linear SVR model by replacing the product $\mathbf{x}_i^T \mathbf{x}$ with the kernel function $K(\mathbf{x}_i, \mathbf{x})$. This is called the kernel trick. Although the parameter C provides a tool for adjusting the complexity of the model, the user often does not have enough control over the final shape of the estimation in many applications. This paper uses the idea of ε-tube to build a regression model whose complexity is prescribed by the user using the prior knowledge that exists about the shape of the motion artifact.

B. Impedance Plethysmography

Impedance plethysmography, i.e., the impedance of body tissue, can be used to extract the respiratory rate when measured on the arms [3]. It can be used to make a portable respiration monitor (an armband) which captures the respiration without imposing any restriction on the movements of the subject. In this method, a small sinusoidal current is injected into the segment of interest using two skin electrodes, called current electrodes. The voltage difference along the path between the current electrodes is then measured using two other skin electrodes, voltage electrodes. Electrical resistance of the tissue is then calculated using the voltage difference between the electrodes which is caused by the passage of the current through the tissue. Changes in the voltage, or similarly the resistance, reflect changes of the blood volume in the segment of interest since electrical conduction of the tissue is mostly contributed by the blood conductivity.

One of the main sources of the blood volume change, in particular in the chest and abdomen area, is respiration. Respiratory rate could be easily extracted from the impedance signal acquired from the chest when subject is motionless. However, motion is another main source of blood volume change which could create drastic changes in the measured impedance signal [4], resulting in changes whose amplitudes are larger than the amplitude of the respiratory signal [5].

The purpose of this paper is to introduce a new motion artifact modeling method which uses the idea of ε-tube to remove simple motion artifacts of rising and dropping the arm that interfere with the impedance signal. Removing more complex motion artifacts in the general case is a future work for this paper.

II. ε-TUBE REGRESSION

The main idea of the ε-TR method is to take advantage of the prior knowledge that often exists about the artifact's general shape in motion artifact reduction. For example, the impedance signal is shown in fig. 1 which is measured on the subject's arms while he is rising his arm and holding it up. The z-axis component of the accelerometer signal can clearly identify the movement of rising the arm, and it is known that rising the arm increases the impedance of the arm tissue [3]. However, the body tries to maintain a constant blood flow into the arm, and brings the impedance level to the baseline as soon as the subject stops moving his hand. As a result, the motion artifact comprises two segments, a rising one and a decaying one with different rising and decaying rates. The target signal to be extracted is the respiration component which surges on top of the motion artifact and has an almost constant amplitude. The algorithm should avoid modeling the variations caused by the respiration and should only model the motion artifact. The motion artifact could be modeled by the combination of two tangent sigmoid functions, one ascending and one descending (fig. 1). The idea of the ε-tube is used so that the respiration wave can lie within the tube and will not be modeled by the algorithm due to the fact that the error is zero inside the tube. In this paper, only simple movements of rising and dropping the arm are considered. As mentioned above, the motion artifact caused by these moves are similar to the shape in fig. 1. Therefore, two neurons with tangent sigmoid AFs are enough to create the model, one of which is ascending and the other one descending. The output of the model is the minimum of the outputs of the two neurons,

$$f(x, \mathbf{w}) = \min(a_1 o_1(x, \mathbf{w}) + b_1, a_2 o_2(x, \mathbf{w}) + b_2) \tag{8}$$

where a_i and b_i are the scale and bias for the ith AF, and o_i is a tangent sigmoid function

$$o_i(x, \mathbf{w}) = \frac{2}{1 + e^{-u_i}} - 1 \text{ and } u_i = w_{i1}x + w_{i2}. \tag{9}$$

The input data x is a scalar here since the problem in hand is one dimensional. The min function is used here instead of Σ

since using the min function prevents neurons from affecting the output of the model outside their working region (before or after the peak), which is desirable in this application.

Using the slack variables as defined in (3), the optimization problem becomes

$$\text{Minimize } R_{\zeta,\zeta^*} = \sum_{i=1}^{n} \zeta_i + \sum_{i=1}^{n} \zeta_i^* \tag{10}$$

such that

$$y_i - f(x_i, \mathbf{w}) \leq \varepsilon + \zeta_i, \quad i = 1..n \tag{11}$$

$$f(x_i, \mathbf{w}) - y_i \leq \varepsilon + \zeta_i^*, \quad i = 1..n \tag{12}$$

$$\zeta_i \geq 0, \quad \zeta_i^* \geq 0, \quad i = 1..n \tag{13}$$

$$a_1 \geq 0, a_2 \geq 0, w_{11} \geq 0, w_{21} \leq 0. \tag{14}$$

Note that the term $\frac{1}{2}\|\mathbf{w}\|^2$ and the parameter C do not exist in ε-TR since the final shape and complexity of the approximation is fixed prior to the learning; thus, smoothness of the model is guaranteed in ε-TR. This is the main advantage of the proposed method since the model avoids modeling the variations caused by the respiration and focuses only on the motion artifact.

The drawback of the proposed method is that the optimization problem is not convex anymore. As a result, the optimization process might lead to local minimums. Thus, choosing a good starting point for the optimization becomes crucial here. We will first introduce a method to decide the tube size, ε, and then discuss the initialization of the optimization problem.

A. Choosing the ε

The size of the tube, ε, depends on the amplitude of the respiration component of the signal. In order to measure this amplitude, the accumulative histogram of the segment of the signal that contains the motion artifact is formed. The shape of the accumulative histogram has two segments. The first segment rises rapidly while the second one has a small derivative. The point at which the two segments are joined is found using piecewise approximation (two pieces) of the accumulative histogram. The first segment is assumed to be associated with the periodic (respiration) component of the signal, while the second one is associated with the motion artifact. Thus, the weighted average of the elements in the first segment is considered to be the bias of the signal, and is removed from the signal. The frequencies of the histogram elements are used as the weights in the calculation of the bias. Next, the standard deviation of the points that fall in the first segment is considered to be the amplitude of the respiration component, and consequently the size of the tube.

B. Initialization of the Optimization Problem

The proposed optimization problem in (10) is a non-convex one. As a result, the initialization of the problem becomes a critical issue which affects both the performance and the quality of the solution. Thus, using a good-quality guess to initialize the optimization problem can increase the performance and the accuracy of the method to a great extent.

First, the signal is scaled such that the peak of the signal is set to be 0.5 and the baseline to be -1. Then, the ascending and descending segments of the motion artifact between $y = -0.5$ and $y = 0.5$ are extracted. The weights of the linear least square approximations of the ascending and descending segments are used for the initialization of the parameters of the two sigmoid functions, as follows

$$w_{i1} = 2s_i \text{ and } w_{i2} = -x_i^* w_{i1} = -2x_i^* s_i \tag{15}$$

where s_i is the slope of the ith segment's linear approximation ($i = 1$ for the ascending segment and $i = 2$ for the descending segment) and x_i^* is its shift where $y_i = 0$. Moreover, the parameters a_1 and a_2 are initialized to 1, while b_1 and b_2 are initialized to 0. Furthermore, ζ_i are set to $\max(0, y_i - f(x_i, \mathbf{w}) - \varepsilon)$, and ζ_i^* are set to $\max(0, f(x_i, \mathbf{w}) - y_i - \varepsilon)$.

III. EXPERIMENTS

The proposed method in this paper is used to remove the motion artifacts from the impedance signal that is measured on the arms. The respiratory rate is then extracted from the filtered signal. The impedance signal is measured by placing two current (injecting) electrodes on the wrists, and two voltage (sensing) electrodes on the arms close to the shoulders. This will allow the subject to freely move his/her arms and other body parts.

Subjects were asked to stay in the siting position, and to breath normally for a while, then raise their arm, breath normally again, and then drop their arm. 18 instances of the movement are collected from 4 healthy subjects and used to assess the proposed method. The subjects were 3 males and 1 female, all 20 to 30 years old.

A Biopac MP150 is used to perform the experiments. The modules that are used are Biopac EBI100C to measure impedance signal and CO2100C to measure the airflow signal. The airflow signal is used as a reference for respiration to measure the accuracy of the proposed method. The sampling rate of the monitor was set to be 1 kHz, and the injected current was 0.1 mA. Moreover, four Kendal 7365 Biotac Ultra Foam ECG electrodes were used in the experiments.

IV. RESULTS AND DISCUSSIONS

In order to assess the effectiveness of the proposed method, the accuracy of the respiratory rate extracted from the impedance signal after removing the motion artifact using ε-TR and the conventional SVR are compared. RBF and polynomial kernels are used with the SVR method. Moreover, a neural network (NN) that consists of two neurons in the hidden layer with sigmoid activation functions is used to create a least squares model. The parameter selection to find the best C and kernel parameters for SVR is done in a subject-wise leave-one-out (LOO) manner, i.e., one of the subjects is left out as the test subject, and several models are trained with the rest of the subjects using different parameter sets. Then the best model is chosen to be tested by the test subject. The process has been repeated for every subject to be the test subject exactly once. The tube size, ε, is chosen

TABLE I

ACCURACY OF RESPIRATORY RATE EXTRACTION

Method	No Filtering	SVR		NN	ϵ-TR
Kernel	-	Polynomial	RBF	-	-
Accuracy	16.4%	33.4%	56.9%	59.68%	86.2%

with the method introduced in section II-A for both ϵ-TR and the conventional SVR.

First, the estimated motion artifact is subtracted from the signal. Then, the respiratory rate is extracted from the filtered signal using short-time-Fourier-transform (STFT). The length of the window is 15s and the window slides 1s each time. The frequency component which has the maximum amplitude is used as the respiratory rate in that window. Respiratory rate is extracted from the reference signal using the same method, and the results are compared to find the accuracy of each method. The results are shown in table I.

The accuracy of extraction of respiratory rate using SVR with Polynomial and RBF kernels is 33.4% and 56.9% respectively. An example of the original signal and the estimations of the motion artifact using NN, SVR with polynomial and RBF kernels and ϵ-TR are shown in fig. 2. The SVR models are generated using the best parameters found. It can be seen that the polynomial kernel is too stiff and has a poor accuracy in approximating the motion artifact. Moreover, it bounces at the boundaries which adds some error to the approximation. The RBF kernel has a better accuracy in approximating the motion artifact. However, it models parts of the respiration component before $t = 5$ and after $t = 20$. The figure clearly shows that ϵ-TR method perfectly models the motion artifact while leaves the respiration component unchanged. Fig. 3 shows the filtered signal using different approximations. It is clear that the red line (filtered using ϵ-TR) closely matches the reference signal while the other two still contain motion artifact.

The proposed ϵ-TR algorithm has many advantages over SVR in motion artifact reduction. First, the shape of the regression model is prescribed in advance; thus, the problem of finding a balance between error and smoothness does not exist here as opposed to SVR. As a result, ϵ-TR does not need the design parameter C and the kernel parameters. Moreover, it solves the problem of lack of control over SV selection since the AFs are chosen in advance. It does not model the respiration component since the AFs are only active during the period in which the motion artifact exits. The disadvantages of ϵ-TR over the conventional SVR algorithm is that the optimization problem is not convex anymore which could lead to local minimums. In addition, solving ϵ-TR optimization problem is more time consuming than SVR since it is not a QP problem anymore.

V. CONCLUSIONS AND FUTURE WORKS

The ϵ-TR method for motion artifact reduction introduced in this paper uses the idea of the ϵ-tube that has been previously used in the SVR algorithm to model the motion

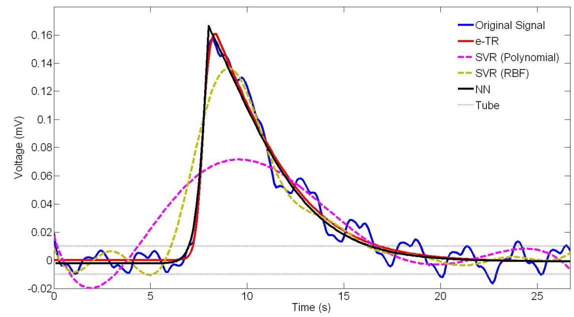

Fig. 2. Motion artifact estimation using different methods

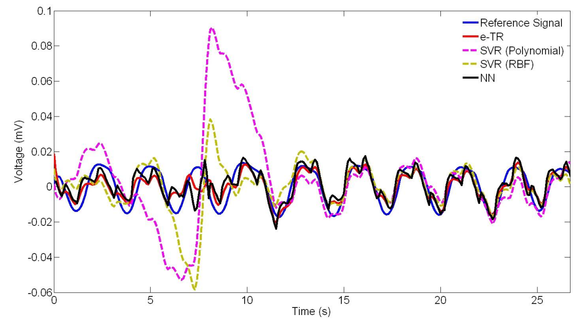

Fig. 3. Signal after filtering using different methods

artifact while leaving the respiration component unaffected. It uses the available information about the shape of the motion artifact to prescribe the shape of the approximation. The results show that ϵ-TR is superior to the SVR and LS algorithms in motion artifact reduction.

The ϵ-TR needs to be expanded to model more complex movements. The combination of multiple AFs can be used to model combined movements. Moreover, the structure of the optimization problem of ϵ-TR needs to be investigated to increase the performance and speed of ϵ-TR. The proposed method needs to be assessed in other applications and with bigger datasets as well. Also, the effectiveness of the proposed method in monitoring patients with tremor, e.g. patients with Parkinson's, needs to be investigated.

REFERENCES

[1] V. Vapnik, *The Nature of Statistical Learning Theory*, Springer-Verlag, New York, NY; 1995.

[2] S. Ansari, A. Belle, K. Najarian and K. Ward, "Impedance plethysmography on the arms: Respiration monitoring", *in Bioinformatics and Biomedicine Workshops (BIBMW), IEEE International Conference on*, Hong Kong, 2010, pp. 471-472.

[3] S. Ansari, K. Najarian, K. Ward and M.H. Tiba, "Extraction of respiratory rate from impedance signal measured on arm: A portable respiratory rate measurement device", *Bioinformatics and Biomedicine, 2009. BIBM '09. IEEE International Conference on*, Washington, DC, 2009, pp. 197-202.

[4] S. Luo, V.X. Afonso, J.G. Webster and W.J. Tompkins, The electrode system in impedance-based ventilation measurement, *Biomedical Engineering, IEEE Transactions on*, vol. 39, 1992, pp. 1130-1141.

[5] J. Rosell, K.P. Cohen and J.P. Webster, Reduction of motion artifacts using a two-frequency impedance plethysmograph and adaptive filtering, *Biomedical Engineering, IEEE Transactions on*, vol. 42, 1995, pp. 1044-1048.