Premature ventricular contraction detection using swarm-based support vector machine and QRS wave features

Nuryani Nuryani* and Iwan Yahya

Department of Physics, University of Sebelas Maret, Surakarta 57126, Indonesia
Email: nuryani@mipa.uns.ac.id
Email: iwanyy@yahoo.com
*Corresponding author

Anik Lestari

Faculty of Medicine, University of Sebelas Maret, Surakarta 57126, Indonesia
Email: leslietarinick@yahoo.com

Abstract: A novel strategy for detecting Premature Ventricular Contraction (PVC) is proposed and investigated. The strategy employs a Swarm-based Support Vector Machine (SSVM). An SSVM is an SVM optimised by using Particle Swarm Optimisation (PSO). The strategy proposes new inputs. The inputs involve the width and the gradient of the electrocardiographic QRS wave. Experiments with different inputs and different SVM kernel functions are conducted to find the best one for PVC detection. On a test using clinical data, SSVM performs well in PVC detection with sensitivity, specificity and accuracy of 98.94%, 99.99% and 99.46%, respectively.

Keywords: PVC; premature ventricular contraction; electrocardiogram; PSO; particle swarm optimisation; SVM; support vector machine.


Biographical notes: Nuryani Nuryani is with the Department of Physics, University of Sebelas Maret, Surakarta, Indonesia. He completed his Doctoral degree from the Centre for Health Technologies, University of Technology, Sydney, Australia. His current research interests include biomedical signal processing, electrocardiography, support vector machine, fuzzy system and evolution techniques.

Iwan Yahya is a Senior Lecturer at Physics Department, Sebelas Maret University. His research interest is acoustics and speech analysis including digital signal processing. He is currently in charge of Acoustics Research Laboratory at Faculty of Science, Sebelas Maret University.
1 Introduction

A Premature Ventricular Contraction (PVC), or a premature ventricular complex, is a premature heartbeat originating from the ventricles of the heart. It disrupts normal rhythm of the heart. PVC in patients with heart diseases might be associated with ventricular tachycardia, which is life-threatening.

PVC detection techniques have been proposed by research groups. A PVC detection technique using Fuzzy Neural Network (FNN) is investigated by Lim (2009) and Shyu et al. (2004). A different technique, an Adaptive Neuro-Fuzzy Inference System (ANFIS) for PVC detection is proposed by Nazmy et al. (2010). PVC detection methods using Support Vector Machine (SVM) are developed by Faziludeen et al. (2013) and Melgani and Bazi (2008). Detection methods using SVM have advantages, such as the ability to generalise well even with a small sample size (Duin, 2000).

This paper proposes a novel strategy for detecting PVC using a Swarm-based Support Vector Machine (SSVM). An SSVM is an SVM where its parameters are optimised using Particle Swarm Optimisation (PSO). Optimisation of SVM parameters is necessary to find the optimal one. An SVM that utilises the optimal parameter could perform better than one that utilises the parameters having randomly given values (Nuryani et al., 2012). The proposed SSVM might outperform the SVM proposed by Faziludeen et al. (2013) as the SSVM utilise PSO. PSO has been used successfully for optimisation in intelligent techniques, such as fuzzy system (Zhao et al., 2010), neural network (Lin and Ming-Hua Hsieh, 2009) and FNN (Kuo et al., 2010). The proposed strategy modifies the method that employs an SVM with PSO investigated by Melgani and Bazi (2008). The modification is mainly conducted by altering the inputs of the SVM and the PSO algorithms. We introduce the width and the gradient of the QRS wave for the SSVM inputs.

The rest of this paper is organised as follows. Section 2 presents the proposed strategy, describing inputs, SVM and PSO. Sections 3 and 4 present the experimental results and discussion, respectively. The conclusion for this paper is drawn in Section 5.

2 Method

This paper presents a PVC detection strategy by employing SSVM, as shown in Figure 1. The inputs in the strategy are the width and the gradient of an electrocardiographic QRS wave. The output is one of two situations: PVC or non-PVC. In the strategy, PSO is used to optimise SVM parameters.
Figure 1  SSVM for detecting PVC with the inputs of the width and the gradient of electrocardiographic QRS waves

2.1 Inputs

The inputs in this strategy are features of the electrocardiographic QRS wave, consisting of the width and the gradient of the QRS wave. Theoretically, QRS width is the interval between the beginning and the end of the QRS wave. In this paper, QRS width is measured in terms of the interval between two defined points at the QRS wave: a defined point in the left side of the QRS wave and another point in the right side (Figure 2). The vertical positions of the two points are at 70% of the peak height of the QRS. The peak of the QRS wave is defined by referring to the data provided by PhysioNet (Moody and Mark, 2001). The measurement approach is chosen to reduce the error caused by frequent error determination of the exact position of the beginning and the end of the QRS wave.

The gradient of the QRS wave is measured in terms of the average of the gradient at two defined points at the QRS wave. The points consist of a defined point in the left side of the QRS wave and another point in the right side (Figure 3). Mathematically, a gradient (or slope) of a line is calculated by finding the ratio of the change in height to the horizontal change. For a QRS wave, the height is the amplitude of the QRS and the horizontal value is time. In this paper, for simplicity, the gradient is measured in terms of the difference in amplitudes of two consecutive points. The horizontal change is the
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space between two consecutive points, where the space between all the points is the same. The gradient is measured at the point located at the vertical position of 70% of the QRS peak, as is also used as reference for measurement of the QRS width.

**Figure 2** Obtaining QRS width by measuring the interval between two defined points in the ascending and descending parts

**Figure 3** Obtaining QRS gradient by measuring the high difference of two consecutive points at the ascending or the descending part

### 2.2 Support Vector Machine (SVM)

The proposed detection strategy is presented in Figure 1. The inputs in this strategy are the width and the gradient of electrocardiographic QRS waves. The output is one of two classes: PVC or non-PVC class. The PVC class indicates that the ECG, represented by the width and the gradient, in the input is grouped as PVC. Conversely, the non-PVC class indicates that the ECG is grouped as non-PVC.

Detail description of SVM can be found in the tutorial by Burges (1998). SVM is a classifier that constructs an optimal hyper-plane which separates binary class data. Let \( X = (x_1, y_1) \) be a set of training data which can be linearly separated, where \( x_i \in \mathbb{R}^m \) is an \( m \)-dimensional space and the associated \( y_i \in [-1, 1] \) is the class label, \( i = 1, 2, \ldots, k \), where \( k \) is the number of data. The optimal hyper-plane can be defined by \( w \cdot x + b = 0 \), which maximally separates the training data; \( w \) is the hyper-plane perpendicular vector. The training data which satisfy \( y_i(w \cdot x + b) - 1 \geq 0 \), lying in the equality of this equation,
are called support vectors. The optimum hyper-plane can be determined through maximizing distance, referred to as margin, between two hyper-planes: \( \mathbf{w} \cdot \mathbf{x} + b = +1 \) and \( \mathbf{w} \cdot \mathbf{x} + b = -1 \). The margin between those two hyper-planes is \( \frac{2}{\|\mathbf{w}\|} \).

For many real-world problems, such separating hyper-planes do not exist. Hence, a slack variable \( \xi_i \) is introduced and then \( y_i(\mathbf{w} \cdot \mathbf{x} + b) \geq 1 - \xi_i \). The optimal separating hyper-plane is determined by minimizing

\[
C \sum_{i=1}^{k} \xi_i + \frac{1}{2} \|\mathbf{w}\|^2
\]

(1)

where \( C \) is a cost constant that is used to control the trade-off between margin size and error.

Searching the optimal hyper-plane is performed using Lagrange multiplier approach through maximizing

\[
L(\alpha) = \sum_{i=1}^{k} \alpha_i - \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \alpha_i \alpha_j y_i y_j (\mathbf{x}_i \cdot \mathbf{x}_j)
\]

(2)

subject to \( 0 \leq \alpha_i \leq C \)

and \( \sum_{i=1}^{k} y_i \alpha_i \)

where \( \alpha_i \) is the Lagrange multiplier.

In case of imbalanced distributions between two class data, which often happens in medical data, a higher error weight \((w_0 \text{ or } w_1)\) needs to be given to the class which has a smaller population (Batuwita and Palade, 2010). Then equation (1) is modified by minimizing

\[
w_0 C \sum_{i:y_i=0}^{k} \xi_i + w_1 C \sum_{i:y_i=-1}^{k} \xi_i + \frac{1}{2} \|\mathbf{w}\|^2
\]

(3)

The inner product in equation (2) needs to be replaced by a kernel function \( K(\mathbf{x}_i, \mathbf{x}_j) \) to map the input data to a higher dimensional space. This mapping is to make it possible to linearly classify the non-linearly separable data. In this paper, four kernel functions are adopted:

Radial basis function (RBF):

\[
k(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2\right)
\]

(4)

Polynomial:

\[
k(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^d
\]

(5)

Sigmoid:

\[
k(\mathbf{x}_i, \mathbf{x}_j) = \left(\gamma (\mathbf{x}_i \cdot \mathbf{x}_j + 1)\right)
\]

(6)
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Linear:
\[ k(x_i, x_j) = x_i \cdot x_j \]  
(7)

The parameters \( C, w_0, w_1 \) in equation (3), \( \gamma \) in equations (4) and (6) and \( d \) in equation (5) are the parameters optimised using PSO.

Finally, the class prediction for any test vector \( x \in R^N \) is given by
\[ f(x) = \text{sgn}(\sum \alpha_y k(x, x) + b) \]  
(8)

where \( \text{sgn} \) is a signum function; the value of \( f(x) \) which is greater than 0 is associated with +1 class (PVC class) and the negative one is associated with −1 class (non-PVC class).

Figure 4  Pseudo-code for PSO used to optimise SVM parameters

```
begin
  t \to 0       // iteration number
  Initialize Z(t)  // Z(t): swarm for iteration t
  Evaluate f(Z(t)) // f: fitness function
while (not termination condition) do
  begin
    t \to t+1
    Update velocity \( v(t) \) and position of each particle \( z(t) \) based on (12) – (15) respectively
    if \( v(t) > v_{\text{max}} \), \( v(t) = v_{\text{max}} \) end
    if \( v(t) < -v_{\text{max}} \), \( v(t) = -v_{\text{max}} \) end
    Evaluate f(Z(t))
    Update \( \hat{z} \) if the new position is better than the previous \( \hat{z} \)
    Update \( z \) if the new position is better than the previous \( z \)
  end
end
```

2.3 Particle swarm optimisation

PSO is used to optimise SVM parameters to find the optimal one. Using the optimal parameters, SSVM could perform well. As mentioned above, the SVM parameters are \( C, w_0, w_1, \gamma \) and \( d \). Essentially, PSO conducts an optimisation considering an evolutionary technique based on the movement of swarms. The optimisation is inspired by the social behaviour of bird flocking and fish schooling (Kennedy and Eberhart, 1995).

The algorithm of PSO can be expressed as in Figure 4. The particles of a swarm \( Z(t) \), representing the SVM parameters, are firstly initialised and then are evaluated by defined fitness function \( f(Z(t)) \). The objective of the optimisation is to minimise the fitness function iteratively. The swarm evolves from iteration \( t \) to \( t + 1 \) by a repeating procedure.

Particles fly through a search space with an adjusted velocity and position. The velocity \( v \) is adjusted by
\[ v(t) = q \left( \phi v(t-1) + c_1 r_1 (z_p - z(t-1)) + c_2 r_2 (z_g - z(t-1)) \right) \]  
(9)
where the position \( z \) is tuned by

\[
z(t) = z(t-1) + v(t)
\]

(10)

where \( z_p \) is the best position of a particle in the previous iteration and \( z_g \) is the best position among all the particles. \( r_1 \) and \( r_2 \) are random numbers in the range \([0, 1]\) and \( \varphi \) is the inertia weight factor. \( c_1 \) and \( c_2 \) are acceleration constants and \( q \) is a constriction factor to ensure the optimisation is converged but not prematurely.

The fitness function of the optimisation is defined in the following:

\[
f = -(S_e + S_p + S_{e_v} + S_{p_v})
\]

(11)

where \( S_e \) and \( S_p \) are sensitivity and specificity, respectively, obtained by an SVM model tested using a training data set and \( S_{e_v} \) and \( S_{p_v} \) are sensitivity and specificity, respectively, obtained by an SVM model tested using a validation data set. The inclusion of \( S_{e_v} \) and \( S_{p_v} \) in the fitness function \( f \) is to reduce the risk of overtraining (Astion et al., 1993). Sensitivity is defined as the ratio of correct detection of PVC to the actual number of PVC cases. Specificity is defined as the ratio of correct detection of non-PVC to the actual number of non-PVC cases.

3 Result

The proposed PVC detection strategy using SSVM has been developed and investigated. The inputs of the strategy are the width and the gradient of the electrocardiographic QRS wave. The inputs are obtained by processing a clinical electrocardiogram. The electrocardiogram is collected from the MIT-BIH database (Lim, 2009; Moody and Mark, 2001). The electrocardiograms of six patients are used. The patients are with the record numbers of 115, 116, 119, 221, 230 and 231, as used by Shyu et al. (2004).

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Width and gradient of QRS waves of normal and PVC beats</th>
</tr>
</thead>
<tbody>
<tr>
<td>Width of QRS wave</td>
<td>Normal: 0.1716±0.0493</td>
</tr>
<tr>
<td>Gradient of QRS wave</td>
<td>Normal: 0.0570±0.0255</td>
</tr>
</tbody>
</table>

Normal and PVC is presented in mean ± standard deviation

A comparison of the QRS width and gradient of both normal and PVC beats is presented in Table 1. The presented values are in the form of normalisation to maximum of 1. The QRS width of PVC beats is wider than that of the normal beats (0.5109±0.0773 vs. 0.1716±0.0493), with the t-test p-value < 0.0001. Conversely, the gradient of the PVC beats is smaller than that of the normal beats. The normal and PVC beats of the collected clinical electrocardiograms are presented in Figure 5. It can be seen that the PVC beats are wider than the normal beats.

To make an SVM model, we employ 20% of the total data set: 10% for training data set and the other 10% for the validation data set. The 20% is taken randomly. The SVM model is created by SVM training and validation, utilising PSO optimisation. The validation is conducted to measure the performance of the SVM model using an unseen
data set. After the optimisation in complete, the SVM model is tested using the testing data set, which is 80% of the total beats. Thus, the SSVM is presented in terms of training, validation and testing stages.

Figure 5  Normal and PVC beats (see online version for colours)

The performances of SSVMs, to detect PVC, with different kernel functions are presented in Table 2. Four kernel functions are investigated to find the most suitable function for the SVM. The functions are RBF, polynomial, sigmoid and linear, which are applied to SSVMR, SSVMP, SSVMS and SSVML, respectively. The performances of SSVMs are measured in terms of sensitivity ($Se$), specificity ($Sp$) and accuracy ($Ac$). The performances involve the performance in training, validation and testing.

Table 2  The performances of SSVMs with different kernel functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Training</th>
<th>Validation</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Se$ (%)</td>
<td>$Sp$ (%)</td>
<td>$Ac$ (%)</td>
</tr>
<tr>
<td>SSVMR</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>SSVMS</td>
<td>100.00</td>
<td>99.91</td>
<td>99.96</td>
</tr>
<tr>
<td>SSVML</td>
<td>100.00</td>
<td>99.83</td>
<td>99.91</td>
</tr>
<tr>
<td>SSVMP</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Notes: $Se$: sensitivity; $Sp$: specificity; $Ac$: accuracy; SSVMR: SSVM with RBF kernel function; SSVMS: SSVM with sigmoid kernel function; SSVML: SSVM with linear kernel function; SSVMP: SSVM with polynomial kernel function.

In general, as indicated in Table 2, the performances of SSVMs with different kernel functions are about the same. Sensitivity, specificity and accuracy of SSVMs are about 100% in training, validation and testing stages. In training and validation stages, the performances of SSVMR and SSVMP are the same and are slightly higher than the other two SSVMs. In the testing stage, the performance of SSVMP is slightly higher than that of the other three SSVMs. Thus, among the four SSVMs, SSVMP performs the best and it is used for the following investigation.

The performances of SSVMP with different inputs are presented in Table 3. SSVMPwg is the SSVMP with the inputs of both the width and the gradient of the QRS wave. SSVMPw and SSVMPg are the SSVMPs with the inputs of the width and the gradient, respectively. SSVMPg performs the worst in terms of sensitivity, specificity and accuracy. SSVMPwg performs slightly better than SSVMPw. Thus, the SSVMP employing the inputs of both width and gradient performs better than that employing a single input.
Table 3  The performances of SSVMs with different inputs

<table>
<thead>
<tr>
<th>Method</th>
<th>Training</th>
<th>Validation</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Se (%)</td>
<td>Sp (%)</td>
<td>Ac (%)</td>
</tr>
<tr>
<td>SSVM Pwg</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>SSVM Pw</td>
<td>100.00</td>
<td>99.74</td>
<td>99.87</td>
</tr>
<tr>
<td>SSVM G</td>
<td>87.10</td>
<td>98.62</td>
<td>92.68</td>
</tr>
</tbody>
</table>

Notes: Se: sensitivity; Sp: specificity; Ac: accuracy; SSVM Pwg: SSVM with the input of width and gradient of QRS wave; SSVM Pw: SSVM with the input of QRS width; SSVM G: SSVM with the input of QRS gradient.

Table 4 compares the performance of SSVMP with the performance of NEWFM proposed by Lim (2009) and FNN proposed by Shyu et al. (2004). NEWFM is a neural network with weighted fuzzy membership functions developed by Lim (2009), and FNN is an FNN developed by Shyu et al. (2004). In general, the performances of the three strategies are nearly the same. Sensitivities of all three strategies are 100% for the records 119, 230 and 231. In terms of sensitivity, SSVMP performs better than NEWFM for the record 221 (98.70% vs. 96.72%), but SSVMP performs worse than NEWFM for the record 116 (94.34% vs. 97.25%). The three techniques perform nearly the same in terms of specificity in all six records, which is in the range 98.73–100%. The three techniques perform about the same in all records, in the range 99.46–100%, in terms of accuracy as well.

Table 4  Comparisons of the performances of SSVM, NEWFM and FNN

<table>
<thead>
<tr>
<th>Record no. (MIT/BIH)</th>
<th>Se (%)</th>
<th>Sp (%)</th>
<th>Ac (%)</th>
<th>Se (%)</th>
<th>Sp (%)</th>
<th>Ac (%)</th>
<th>Se (%)</th>
<th>Sp (%)</th>
<th>Ac (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SSVM</td>
<td>NEWFM</td>
<td>FNN</td>
<td>SSVM</td>
<td>NEWFM</td>
<td>FNN</td>
<td>SSVM</td>
<td>NEWFM</td>
<td>FNN</td>
</tr>
<tr>
<td>115</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>99.95</td>
<td>99.69</td>
<td>99.95</td>
<td>99.95</td>
<td>99.69</td>
<td>99.95</td>
</tr>
<tr>
<td>116</td>
<td>94.34</td>
<td>97.25</td>
<td>95.41</td>
<td>100.00</td>
<td>99.87</td>
<td>99.69</td>
<td>99.75</td>
<td>99.79</td>
<td>99.49</td>
</tr>
<tr>
<td>119</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>221</td>
<td>98.70</td>
<td>96.72</td>
<td>98.74</td>
<td>97.84</td>
<td>98.70</td>
<td>99.60</td>
<td>98.45</td>
<td>99.46</td>
<td>99.38</td>
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<tr>
<td>230</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>99.73</td>
<td>–</td>
<td>99.96</td>
<td>99.69</td>
<td>99.96</td>
<td>99.96</td>
</tr>
<tr>
<td>231</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Notes: SSVMR: SSVM with RBF kernel function; NNWFNM: neural network with weighted fuzzy membership functions developed by Lim (2009); FNN: fuzzy neural network developed by Shyu et al. (2004).

4 Discussion

The performance of the SSVMP (SSVM with polynomial kernel function) is better than that of the other three SSVMs, employing RBF, sigmoid and linear kernel functions. The reason might be that the result of the polynomial function mapping is more likely to be correctly classified by SVM than the other kernel function mappings. Furthermore, SSVML could be a special case of SSVM, which means that SSVM could have more possibilities of obtaining a better performance than SSVML. The better performance of the proposed SVM-based system which employs a polynomial kernel function is confirmed in other applications (Ke-wu, 2009).
The proposed swarm optimisation could work as desired. It is indicated by high sensitivity and specificity obtained by the SSVM algorithms. In the optimisation, PSO employs sensitivity and specificity for its fitness function, as defined in equation (11). It means that PSO conducts an effort to find high sensitivity and specificity. High sensitivity of a PVC detector shows that it has high true positive. High true positive indicates that PVC beats can be detected properly. High specificity in a PVC detector minimises false alarm, which is a non-PVC beat recognised as a PVC beat.

The computational time required by the PSO optimisation depends on the number of iteration and the time consumed by every iteration. Every iteration conducts SVM training to make \( n \) SVM models; \( n \) is the number of particles of PSO. The number of particles is 50. The iteration number is 200, and hence, after 200 iterations, the optimisation terminates.

The SSVM applying both inputs, the width and the gradient of the QRS wave, performs better than that applying a single input, either the width or the gradient. The performance of the SSVM applying only the width only is better than that of the SSVM applying only the gradient. It could imply that the width of the QRS wave contributes more significantly than the gradient, in providing a better performance in PVC detection.

The proposed detection methods introduced in this paper provides similar performance to the NEWFM and FNN methods, proposed by Lim (2009) and Shyu et al. (2004), respectively. In terms of algorithm, SSVM applies a hybrid of PSO and SVM; the other two methods apply a hybrid of fuzzy and neural network. In terms of inputs, SSVM uses an electrocardiogram signal directly, whereas the other two methods employ wavelet transform coefficients of electrocardiogram. Applying a electrocardiogram signal directly could provide a lower computational cost than applying a wavelet transform coefficient. A low computational cost is important for a detection system in clinical diagnosis (Butko et al., 2009).

The width and gradients are obtained from the QRS wave normalised to a maximum of 1. The normalisation is essential to reduce the effects of altered QRS wave amplitudes and altered baseline wander. By normalisation, the computation is simpler and less complex, which is easier to be implemented for device development.

The SVM model for PVC detection is obtained by SVM training. The training used electrocardiographic clinical data. The SVM model can be used to indicate whether the electrocardiogram in the input belongs to PVC or non-PVC. Thus, principally the proposed strategy could be implemented for PVC detection.

Design of the PVC detection presented in this paper is not yet in a real-time form. A real-time algorithm is important for device development. Thus, this work needs further studies to implement the proposed technique in a real-time system.

5 Conclusion

This paper has presented a strategy to detect PVC in electrocardiogram. An SSVM is implemented for PVC detection. In the SSVM, PSO is employed to optimise the SVM parameters. Comparing four kernel functions, the SSVM applying polynomial kernel function performs better than that applying the other three kernel functions: RBF, sigmoid and linear kernel functions. Employing the width and the gradient of the electrocardiographic QRS wave, SSVM finds the performance of 98.94%, 99.99% and 99.46% in terms of sensitivity, specificity and accuracy, respectively. A further study could be conducted by implementing the proposed algorithm in a real-time device.
References


