EMG Signals Gaussian Filtering for Improved Hand Gesture Classification

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***Abstract*—This article addresses the classification problem of human hand movements using electromyography (EMG) signals that are usually contaminated with notable noise. Such contamination results in a significant classification performance degradation when using the sensed EMG signals in classifying EMG signals of human hand gestures. In order to enhance the classification performance, Gaussian Smoothing Filter (GSF) is employed in filtering out the noise of the sensed EMG signals and then the resulted filtered signals, along with the available classification schemes, are used for classifying the phases of hand gestures. The main features of the GSF are the high filtering efficiency, simple implementation and equal support in both frequency and time domains which gives the GSF the privilege of simultaneously filtering out the noise while keeping the high frequency components of the signal. In addition to improving the classification accuracy, employing the GSF results in smoothed EMG signals reducing the computational time required for developing/testing the classification process. Experiments are conducted on classifying EMG signals, captured from a MYO band, using multiple classification techniques and a significant improvement is observed in the classification performance when using the GSF for filtering out the noise of the EMG signals. Comparison is conducted with the EMG classification when the GSU is not used in smoothing the sensed EMG signals and the significant enhancement of the classification performance is shown. Furthermore, a significant reduction in the computational time is reported when employing the GSF-based classification entrenching the advantages of the GSF for the classification of EMG signals.**

***Index Terms*- Classification; EMG signals; Gaussian filter; Signals smoothing.**

I. Introduction

The Electromyography (EMG) is an approach of recording the electric response of the muscles by computing the electric potential resulted by their cells when they are activated and engaged in a certain action [1]. The resulted EMG signals were successfully applied to many diversified applications e.g. neuromuscular monitoring during the anesthesia [2], computer interface for limb disabled situation [3], function of nerves measurements using an EMG needle [4], robots control [5], to name a few. Most of these applications study the statistical features of the sensed EMG signals and develop data-driven models that are suited to the application needs. One of these data-driven models is the EMG signals classification which is considered one of the attractive elements in multiple EMG signals-based applications [6].

One of the earliest efforts for classifying EMG signals was reported by Graupe and Cline when they employed the autoregressive-moving-average (ARMA) in building a parametric classification approach for interpreting the EMG time series signal [7]. Using various time-frequency representation, promising classification performance was reported employing Fourier and wavelet transforms [8]. In [9], a real-time EMG signals-based approach was developed for simultaneous detecting multiple hand motions and learning to adapt to the human situation with an application to prosthetic hand that gave good results. Hidden Markov and autoregressive models were combined for developing efficient models of human hand gesture using the sensed EMG signals and promising resulting were reported [10]. In [11], Support Vector Machine was efficiently employed in real-time classification of EMG signals for distinguishing human hand gestures while the arm joint angles were estimated by developing simple linear models relating the EMG signals to the joint angles. Other techniques were efficiently suggested for classifying EMG signals like K-Nearest Neighbor (KNN) [12], Linear Discriminant Analysis (LDA) [13], Deep Neural Network (DNN) [14], among others.

This article suggests improving classifying the EMG signals, when using the classification schemes above, that are frequently contaminated with a significant amount of noise degrading the performance of the classification process. The EMG signals classification is established by employing Gaussian Smoothing Filter (GSF) for filtering out the noise encountered in EMG signals. The main features of the GSF are its simplicity in implementation, its time and frequency domain supports similarity, and excellent noise suppression performance. These features are great driving force behind the applicability of the GSF to the EMG classification since the signals in the latter, and as will be seen, encounters a significant noise degrading the classification performance. Moreover, employing the GSF will be shown to reduce the computational cost required for training and testing the models.

The rest of the article is organized as follows: Section 2 describes the EMG signals classification problem and the noise encountered in EMG signals. Section 3 explains the GSF and several classification techniques, namely Support Vector Machine (SVM), Naive Bayes Classifier (NBC), Linear Discriminant Analysis (LDA), and k-Nearest Neighbor (k-

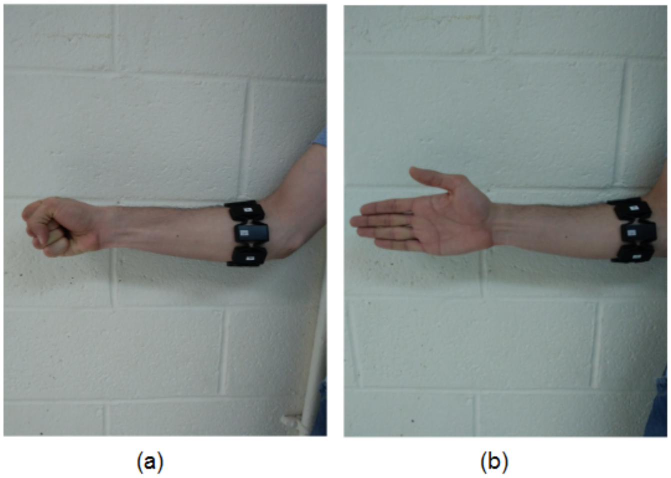

Figure 1. MYO band mounted on an arm with: (a) Hand closed, (b) Hand opened.

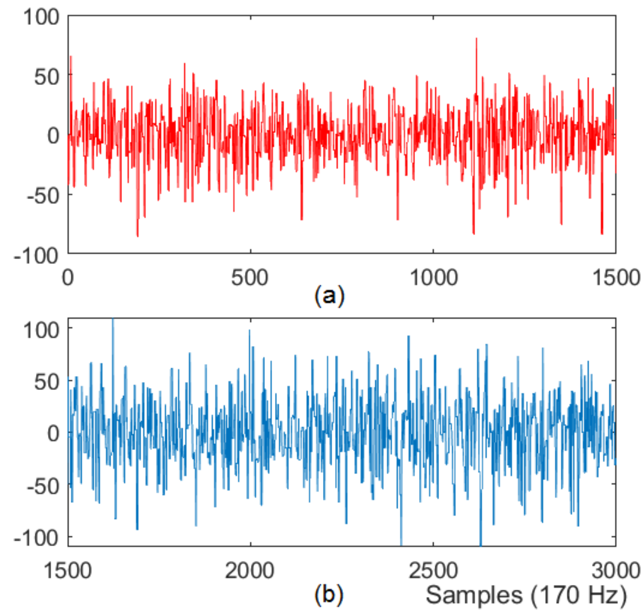

Figure 2. The EMG signals of Figure 1: (a) Hand closed, (b) Hand opened.

NN), used for EMG signals classification. Section 4 details the experimental validation and the enhancement in classification when using the GSF in smoothing the EMG signals. Finally, Section 5 contains concluding remarks and recommendation for future works.

II. Problem Description

Let's consider the sensed signal of the human hand movement shown in Figure 1 which is composed of two phases of movements: (a) in which the hand is closed and (b) where the hand is opened. The corresponding sensed signal of one of the MYO band sensors corresponding to phases (a) and (b) are shown in Figure 2 (a) and (b), respectively. One can formulate the problem of classifying the phases shown in Figure 1 (a) and (b) to be:

$$y_{\text{phase}_\text{i}}(t) = \begin{cases} 1, & \text{if } x(t) \in \text{phase}_\text{i} \\ 0, & \text{Otherwise.} \end{cases} \tag{1}$$

Where $y_{\text{phase}_\text{i}}(t) \in R$ is the desired classifier output of the i^{th} phase at time instance t and $x \in R^8$ is the corresponding EMG signal vector [1]. Thus, the main objective of the classification process is to develop models that can realize the nonlinear mapping given in (2) as accurate as possible. However, it is obvious from Fig 2 (a) and (b) that the sensed EMG signals are contaminated with a noise that degrades the performance of the classification process. Therefore, the main objective of this article is to enhance the classification process by filtering out the noise from the sensed EMG signal employing the GSF before conducting the classification stage.

III. GSF-Based Enhanced Classification Process

In order to detail the suggested GSF-based enhanced classification approach, related topics are, firstly, explained namely the concept of the GSF with multiple classification techniques. Then, both of the GSF along with the available classification techniques are used in order enhance the process of distinguishing the hand gestures using the EMG signals.

A. Gaussian Smoothing Filter (GSF)

The GSF can be described by the following impulse response [15]:

$$g(x(t)) = \frac{e^{\frac{-x(t)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}. \tag{2}$$

Where $x(t)$ is the signal to be smoothed and σ is the standard deviation of the GSF. Obviously, (2) represents the impulse response of the considered filter and one can use the convolution in order to obtain the filter output as:

$$\hat{x}(t) = x(t) \circledast g(x(t)), \tag{3}$$

with $\hat{x}(t)$ is the output of the GSF and $\circledast$ is the convolution which can be obtained by:

$$\hat{x}(t) = \int_{-\infty}^{\infty} x(\tau) g(x(t-\tau)) d\tau. \tag{4}$$

Suppose that we are given the vector of signals x captured from noisy sensors and consider that x is required to develop a classifier with the corresponding target output y. Figure 3 shows the impulse response of the GSF and taking the Fourier transform for (2), we obtain:

$$G(f) = e^{-\pi^2 f^2 \sigma^2}, \tag{5}$$

with f is the frequency. (5) is obviously also a Gaussian function that leads to the fact that both of the time and frequency domain responses are having a similar support

[1] It is worth noting that we have $x \in R^8$ since the MYO band considered throughout the article is composed of 8 sensors and for cases where we have p EMG sensors in the device then x would be a p-dimensional vector, i.e. $x \in R^p$.

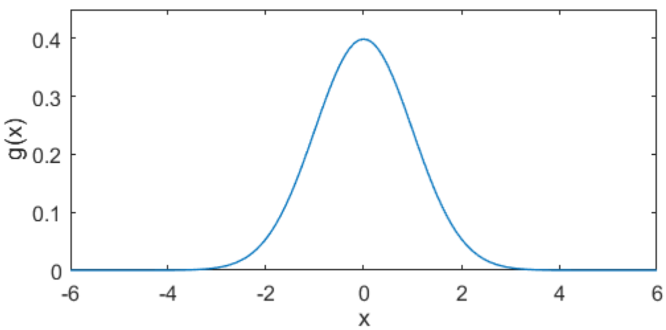

Figure 3. An example of the impulse response of a Gaussian smoothing filter with $\sigma = 1$.

which is a Gaussian function. Therefore, the GSF is able of smoothing a noisy signal while keeping the high frequency components of the original signal.

B. Filtered EMG Signals Classification

Using (4), one can rewrite (2) in terms of the filtered signal as:

$$y_{\mathrm{phase_i}}(t) = \begin{cases} 1, & \text{if } \hat{x}(t) \in \mathrm{phase_i} \\ 0, & \text{Otherwise.} \end{cases} \tag{6}$$

In order to realize (6), the available classification techniques can be employed for developing models approximating (6) as accurate as possible. In the pattern classification literature, there are many schemes that can be employed for such a classification task and below is a brief summary of four well-known classification schemes and further details can be found in classification and statistical modeling literature (See [16], [17]):

1) Support Vector Machine (SVM): Given the training data set $D = \{(x_1, y_1), ..., (x_N, y_N)\}$, the SVM classification technique can be formulated as a solution to the following optimization problem [18]:

$$\min_{\mathbf{w},\xi_\mathrm{i}} J(w, \xi_i) = \|w\|^2 + C \sum_{i=1}^{N} \xi_i, \tag{7}$$

subject to:

$$y_i f(w^T x_i) \geq 1 - \xi_i. \tag{8}$$

Where (w, ξ_i) are the SVM parameters with $\xi_i \geq 0$ and C is a constant vector. Therefore, estimation of w and ξ_i for a given training set produces the information on the boundaries for class separation, which yields good classification performance. It is worth noting that solving the optimization problem above can be realized by multiple schemes. Frequently, the Lagrange multiplier optimization method is employed for solving the optimization problem above resulting in excellent classification performance.

2) k-Nearest Neighbor (k-NN): Given the set of data D, the k-NN can be employed in estimating the output of a classifier as:

$$\hat{y}(x_i) = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i. \tag{9}$$

Where $\hat{y}(x)$ is the classifier output, $N_k(x)$ is the neighborhood containing k elements of x, k is the total number of elements of the neighborhood, and y_i is the class label corresponding to x_i. The neighborhood can be specified using Euclidean:

$$d(x_i, x_j) = \sqrt{\sum_{i=1, i\neq j}^{k} (x_i - x_j)^2}, \tag{10}$$

Manhattan:

$$d(x_i, x_j) = \sum_{i=1, i\neq j}^{k} |x_i - x_j|, \tag{11}$$

Minkowski:

$$d(x_i, x_j) = (\sum_{i=1, i\neq j}^{k} (x_i - x_j)^p)^{\frac{1}{p}}, \tag{12}$$

distance measures, among others.

3) Naive Bayes Classification (NBC): Suppose that K is the total number of possible categories, or labels, that y_i can take and let π_k be the prior probability that x_i corresponds to the k^{th} class with $k = 1, 2, \ldots, K$. Denote $f_k(x) = p(x = x_i | y = c_k)$ as the density function of x obtained from the k^{th} class where c_k is the label of the k^{th} class of y. Using Bayes rule, one can have:

$$p(y = c_k | x = x_i) = \frac{\pi_k f_k(x)}{\sum_{j=1}^{K} \pi_j f_j(x)}. \tag{13}$$

$p(y = c_k | x = x_i)$ is called the posterior probability that suggests $y = c_k$ given the predictor x_i. Therefore, the class with the largest posterior probability for a predictor x_i is judged to be the class to which the predictor x_i corresponds and this is called the Naive Bayes Classification (NBC). $f_k(x)$ is a key factor in specifying the accuracy of classification and one of the simplest, yet efficient, scheme is to employ the Gaussian function for approximating $f_k(x)$.

4) Linear Discriminant Analysis (LDA): The LDA classification is developed based on the NBC. If one assumes the data x drawn from a Gaussian distribution and taking the log of (13), one can obtain:

$$\hat{\delta}_k(x) = x\frac{\hat{\mu}_k}{\hat{\sigma}_k^2} - \frac{\hat{\mu}_k^2}{2\hat{\sigma}_k^2} + log(\hat{\pi}_k), \tag{14}$$

where:

$$\hat{\mu}_k = \frac{1}{n_k} \sum_{i:y_i = c_k} x_i, \tag{15}$$

$$\hat{\sigma}^2 = \frac{1}{n - K} \sum_{k=1}^{K} \sum_{i:y_i = c_k} (x_i - \hat{\mu}_k)^2, \tag{16}$$

$$\hat{\pi}_k = \frac{n_k}{N}, \tag{17}$$

n_k is the number of training samples of the k^{th} class. A sample is deemed to belong to a certain class if (14) is largest for that class. This is why (14) is called a discriminant and its linearity with respect to the predictor gives the linear attribute of the LDA classification process.

Table I
ENHANCEMENT OF EMG SIGNALS CLASSIFICATION.

Scheme	Performance (%) without GSF	Performance (%) with GSF
SVM	79.82	94.52
LDA	83.33	93.19
NBC	86.31	93.79
k-NN	93.56	98.09

Table II
ACCUMULATIVE COMPUTATIONAL TIME.

Scheme	Time (sec) without GSF	Time (sec) with GSF
SVM	402.955610	381.108461
LDA	9.333651	4.141514
NBC	10.624116	6.537230
k-NN	10.178241	5.135755

IV. EXPERIMENTAL VALIDATION

In order to evaluate the performance of the GSF and its impact on the EMG classification problem in hand gesture recognition, let's consider the scenario shown in Figure 4 that is having six distinct hand gestures: flexion, extension, wrist flexion, wrist extension, pinching, and index extension that are named in this article as Phase 1, 2, 3, 4, 5, and 6, respectively. A MYO band, containing eight EMG sensors, is used for capturing the EMG signals of the hand during the aforementioned hand gestures. Figure 5 shows the unfiltered EMG signals for all six phases of the hand gestures considered in this article.

Employing the SVM, LDA, NBC, and k-NN in classifying EMG signals of Figure 5 resulted in classification accuracy of 79.82%, 83.33%, 86.31%, and 93.56%, respectively. Using the GSF with $\sigma = 2$, that was manually selected, we obtained the EMG signals shown in Figure 6. As per employing the filtered EMG signals, shown in Figure 6 for classifying the hand gestures under consideration, we obtained classification accuracy of 94.52%, 93.19%, 93.79%, and 98.09% when using the SVM, LDA, NBC, and KNN classification techniques, respectively. It is obvious that when employing the GSF in the EMG classification process, a significant improvement results for all four classification techniques considered in this article. Such a classification performance enhancement is a consequence of filtering out the noise from the EMG signals. Table I summarizes the classification accuracy of the aforementioned techniques with and without using the GSF in filtering out the noise. The GSF filter has only one parameter, say the standard deviation σ, and its implementation is simple that facilitates developing its algorithm for the EMG signals classification task. However, the main reason behind the efficient performance when employing the GSF in filtering out the noise stems from the nature of the similarity of supports in both time and frequency domains, i.e. both of them are Gaussian functions, since the frequency transform of a Gaussian function is Gaussian as well. Therefore, high frequency noise is eliminated without suppressing and deteriorating the corresponding EMG signal quality rendering efficient noise filtering process that is reflected on the EMG classification task.

Measuring the time required for developing and testing the models of the unfiltered EMG signals resulted a total computational time of 402.955610 sec when using the SVM, 9.333651 sec for the LDA, 10.624116 sec when employing the NBC, and 10.178241 sec in the case of k-NN. The corresponding time required for developing and testing the models for the case of filtered EMG signals was found to be 381.108461 sec when using the SVM for classifying the EMG signals, 4.141514 sec for the case of LDA classifier, 6.537230 sec when employing the NBC while the k-NN required 5.135755 sec for developing and testing the models. Table II summarizes the time required for developing and testing the models for the cases before and after employing the GSF when using the SVM, LDA, NBC, and k-NN in the EMG signals classification task. It is obvious from Table II that the measured computational time is reduced significantly, for all classification techniques, when using the GSF in filtering out the noise from the sensed EMG signals. The rate of approximation r_n in a learning process is related to the smoothness of a signal by the relation [19]:

$$r_N = N^{-\frac{s}{N_d}}, \tag{18}$$

where s is a smoothness measure of the signal and N_d is the dimensionality of the input training space. Thus for a fixed N and N_d, according to (18) one can deduce that

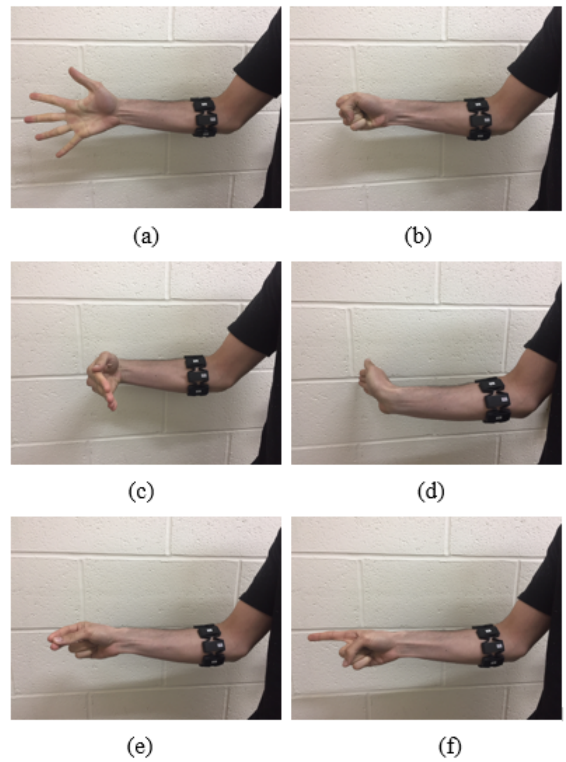

Figure 4. MYO band with multiple situations: (a) Flexion, (b) Extension, (c) Wrist flexion, (d) Wrist extension, (e) Pinching, and (f) Index extension.

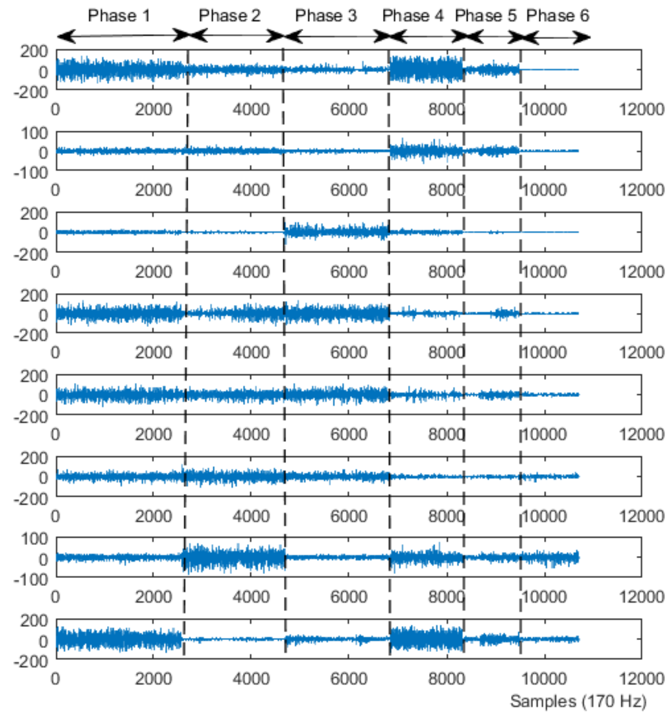

Figure 5. The unfiltered MYO band EMG signals.

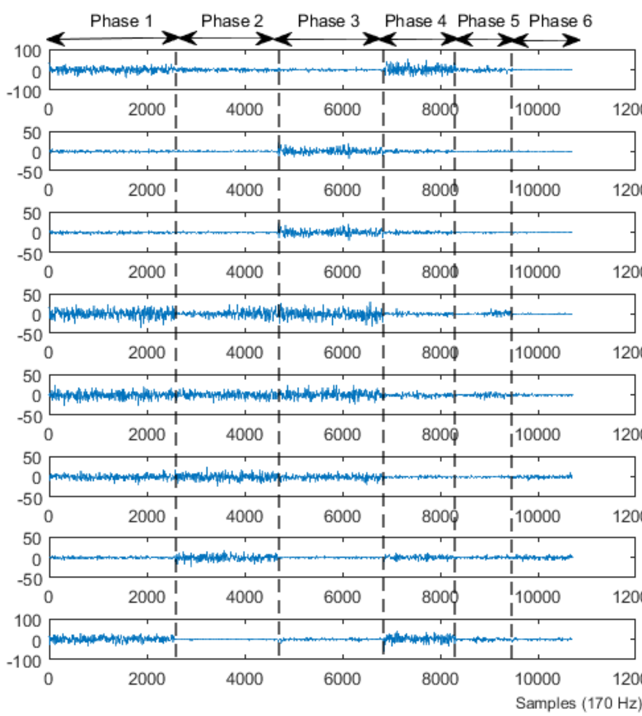

Figure 6. The filtered MYO band EMG signals.

increment in the smoothness s of the EMG signals results in decrement of the rate of approximation r_n leading to a faster approximation of the risk functional of the EMG classification process[2]. When employing the GSF, the value of s increases resulting in reduced values of r_n which speeds up the process of approximating and minimizing the risk functional of the classification process.

V. Conclusion and Future Works

In this article, Gaussian Smoothing Filter (GSF) is employed in enhancing the Electromyography (EMG) classification process. The sensed EMG signals are shown to be contaminated with a significant amount of noise that is shown to result in a degraded performance. Employing the GSF, the noise of the EMG signals is filtered out that results in enhanced classification process and the main reason behind such enhancement is degrading the undesirable/unpredictible effect of noise on the EMG signals. Experiment is conducted on a MYO band classification scenario consisting of six distinct hand gestures and in order to have a concrete impression of the performance of the GSF, four EMG signals classification techniques are addressed: Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Naive Bayes Classifier (NBC), and k-Nearest Neighbor (k-NN). The classification performance was found to be 79.82%, 83.33%, 86.31%, and 93.56% when using the SVM, LDA, NBC, and k-NN, respectively in classifying the sensed EMG signals without filtering out the noise. As per employing the GSF for smoothing the EMG signals, the classification performance was found to be 94.52%, 93.19%, 93.79%, and 98.09% with the SVM, LDA, NBC, and k-NN, respectively that gives a very good impression of the enhancement brought about due to employing the GSF in filtering out the noise of EMG signals. Furthermore, employing the GSF is shown to reduce the computational time of the learning process that adds another advantage to the proposed EMG filtering strategy.

Despite the excellent performance reported in this article in employing the GSF, its standard deviation is not optimized that might affect the filtering process and non-optimal classification might result. Therefore, future works will focus on developing an enhanced GSF algorithm where the optimal value of the standard deviation is estimated and integrated in the classification process.

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[2]See [18] for more details about the relation between the risk functional approximation and the smoothness of a function.

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