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Assessment on Stationarity of EMG Signals with Different Windows Size During Isotonic Contractions

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Abstract: In order to analyse surface electromyography (EMG) signals, it is necessary to extract the features based on a time or frequency domain. These approaches are based on the mathematical assumption of signal stationarity. Stationarity of EMG signals is thoroughly examined, especially in isotonic contractions. According to research, conflicting results have been identified depending on varying window sizes. Therefore, in this study, the authors endeavoured to determine the suitable window size to analyse EMG signals during isotonic contractions utilising stationary tests, reverse arrangement (RA), and modified reverse arrangement (MRA). There were slight differences in the average percentages of signal stationarity for RA and MRA tests in 100 ms, 500 ms, and 1000 ms window sizes. However, there was none for the 200 ms window size. On average, a window size of 200 ms provided stationary information with 88.57% of EMG signals compared to other window sizes. This study also recommended the MRA test to determine EMG signals stationarity for future studies, as the performances were better in comparison to RA tests. However, the following recommendation is only valid for window sizes greater than 200 ms. For a real-time application, the size of the analysis window together with the processing time should be less than 300 ms and a window size of 200 ms is applicable for isotonic contractions.

Keywords: EMG signals; isotonic contractions; stationary; windows size

1. Introduction

In recent years, there has been an increasing interest in the analysis of electromyography (EMG) signals in clinical and engineering applications. EMG signals reflect electrical currents emanating in muscles during neuromuscular activities such as muscle activation, contraction, or relaxation. These EMG signals are the summation of motor unit action potential controlled by the central nervous system which can be obtained through two techniques—namely, invasive and non-invasive. The non-invasive approach is preferable, as it offers benefits such as a minimal risk of infection and avoids discomfort for amputees [1]. Surface EMG signals are not only used to diagnose patients with neuromuscular diseases [2,3] and detect muscle fatigue [4], but also assist individuals who suffer from limb amputations and are using robotic devices or assistive technological devices during rehabilitation [5,6]. The major difficulty of applying these bio-signals in a pattern recognition system in real time is that they are unstable and vary in time [7]. A conflicting result was found inthe study conducted in [8]; Android™-based mobile devices were developed for stationary bicycle exercise using EMG and electrocardiography (ECG) signals and demonstrated that the devices were able to calculate the cadence and heart rate for biking in real-time application, with detection rates of 91% and 94%, respectively. In addition, assistive devices such ankle-foot orthoses were developed by Dimas et al. utilising the concept of controlling output voltages based on EMG signals and ankle position as shown in Figure 1 [9]. Their system successfully controlled the output voltage according to the required needs. However, a problem arose in analysing EMG signals when EMG signals were interpreted through general observation.

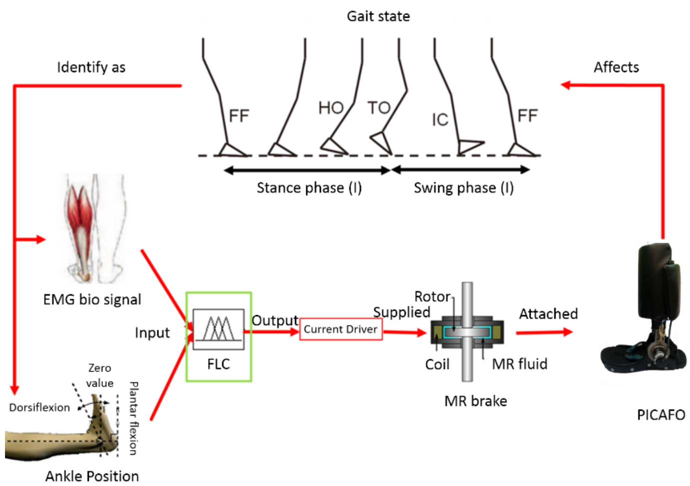

Figure 1. An overview process on the development of AFO as conducted in [9]. FF: Foot Flat; HO: Heel Off; TO: Toe Off; IC: Initial Contact; PICAFO: Passive Controlled Ankle Foot Orthoses; FLC: Fuzzy Logic Controller; MR: Magnetorheological.

Numerous studies have proposed various techniques to obtain a higher accuracy in detecting surface EMG pattern recognition [1]. In the development of the prosthetic hand, the usage of multiple EMG sensors is not practical and makes it difficult for amputees due to electrode shift/movement, and amputees often feel discomfort in wearing the surface EMG sensor. This problem was resolved by applying independent component analysis and Icasso clustering to select the optimum number of sensors, and two sensors gave a higher average accuracy than others (96.6%) [10].

Generally, the main processes involved in pattern recognition are feature extraction and classification. Features are extracted from the surface EMG signals and trained into a classifier to recognise different patterns of muscle activities. It has been pointed out that feature extraction plays a crucial role in achieving better classification performances [11]. This process involves the transformation of raw EMG signals into a feature vector. Various features based on either time domain (TD) or frequency domain (FD) and time-frequency domain (TFD) are utilised. According to He et al., the relative changes in EMG signal features over time become progressively smaller when the number of days during which the subjects perform the pre-defined motions increases [12]. Meanwhile, a self-recalibration using TFD features and a convolutional neural network classifier was proposed in [13] that can be automatically updated to maintain a stable performance over time without the need for a user retraining base. Similarly, with the study conducted in [14], the principal component analysis of TFD features showed the best linear relationship with the grasp types compared to TD and FD features for grasp recognition. However, TFD features yield a high-dimensional feature vector [1]. Thus, TD features are mostly adopted in the literature, as discussed in [15].

TD features were evaluated based on signal amplitude that varied with time. In 1993, Hudgins et al. proposed five TD features—namely, mean absolute value, mean absolute value slope, slope sign changes, zero crossing, and waveform length [16]. They demonstrated that extracting EMG signals using TD was promising in prosthesis control. After that, many types of TD features were applied for bio-signal-based control in assistive devices, as discussed in [17]. The classification accuracy of TD features was not only higher than FD features, but also allowed grouped classification according to mathematical properties into four main types: energy information, frequency information, prediction model, and time-dependence methods [18]. In comparison with TFD features, TD features achieved classification accuracy of approximately 97% in discriminating upper limb movements [19], which were higher than TFD features that only gained average accuracy 78.1% [20]. However, an underlying assumption of TD features is that the signal analysed is stationary, making it inappropriate to be employed for EMG signals that are non-stationary in nature. Furthermore, it has been observed that EMG signals are stationary for short periods of time [21].

In many studies, EMG stationary state signals are seldom tested and are more often presumed. A stationary signal is characterised as an equilibrium condition, whereas the statistical properties are time invariant. There are four categories involving stationary process: first-order, second-order, wide sense (WSS) and strict stationaries [22]. In practice, WSS is deemed adequate for signal analysis when the statistical moments that describe the signals do not change over time, as implemented by Martin et al. in 1997 [21]. That approach was represented as weakly stationary used in the present studies. Run, reverse arrangement (RA), and modified reverse arrangement (MRA) tests are mostly adopted to determine whether EMG signals satisfy the stationarity conditions [23]. Nonetheless, conflicting results of the stationarity of EMG signals have been observed for different window sizes, types of contraction, and the load exerted.

In general, there are three types of contractions: isometric, isotonic, and isokinetic. Isotonic contraction involves a change in muscle length (e.g., shorten and lengthen) produced during dynamic movements or exercise. If the speed remains constant, the contraction is defined as isokinetic contractions. Specific equipment is required to measure these contractions; for example, Humac Norm testing and rehabilitation using trunk module [24]. The study revealed that the stationarity of EMG signals decreases as trunk extension angular velocity increases as much as 30 degrees with 1000 ms window size based on RA and MRA tests. In the case of isometric contraction which occurs during static positions (the joint angle and muscle length do not change), the stationarity level of EMG signals depends on the window size [25]. With 375 ms and 125 ms window size, EMG signals are reported as stationary during isometric and isotonic contractions, respectively [26].

On the other hand, the reported classifier performance was influenced by the segment length or window size. Farina and Merletti pointed out that the classifier performance degraded when using a window size less than 125 ms, as observed in the case of high non-stationarity [27]. This statement was proven by Phinyomark et al., as the accuracy of classification increased by about 2–3% and $\leq$1% for segment length from 125 to 250 ms and from 250 to 500 ms, respectively [28]. They stated that the result was due to a larger segment providing additional information while yielding small bias and variance in the estimation of the feature. Similarly, with the research conducted in [29], the window size between 128 ms and 256 ms gained lower percentages of error compared to the segment length that was less than 128 ms during steady and transient states.

Steady-state data were collected during constant force contraction and transient state during muscle activity from relaxing to voluntary contraction level. It was reported that 200 ms segment length held a desirable muscle contraction in comparison to 50, 100, 150, 300, and 500 ms for isometric contractions [19]. The aforementioned result agreed with previous studies that analysed EMG signals within 200 ms window size in classifying stages of contractions in wrist muscles [30] and walking gait event [31]. However, there were no discussions about the stationarity of EMG signals for 200 ms window size. Thus, it is necessary to determine whether the EMG signals in this window size are stationary or otherwise.

The aim of this study was to investigate the stationarity of EMG signals during isotonic contractions. Therefore, an attempt was made to answer the question of whether extracting

EMG signals based on TD was feasible in pattern recognition, especially in isotonic conditions. As highlighted earlier, TD features assumed the signals were stationary and the window size affected the stationarity of EMG signals. For this purpose, the authors explored acceptable window sizes in which the EMG signals remain stationary. This study compared the performances between RA and MRA tests.

2. Materials and Methods

2.1. Data Acquisition and Processing

Seven male subjects (age = 23.6 ± 3.4 years, height = 1.65 ± 0.2 m; mean ± sd) participated in the experiment with inclusion criteria of no history of physiological or nerve injury that may have affected gait. The surface EMG signals were detected by placing Ag/AgCl electrodes on the gastrocnemius medialis (mGas) muscle of the right leg together with a reference electrode at the patella in accordance with surface electromyography for the non-invasive assessment (SENIAM). The contact point of the electrodes was prepared by shaving and cleansing the skin with alcohol beforehand in order to reduce the impedance on the skin surface. The online processing of surface EMG signals was provided by EMG device (Nihon Kohden, Saitama, Japan) with inter-electrode distances of 1 cm and amplified by a multichannel amplifier with bandwidth filter from 15 to 1000 Hz. Then, EMG signals were connected to 64Ch analogue-to-digital converter as shown Figure 2. The experimental protocol was approved by the local ethical committee.

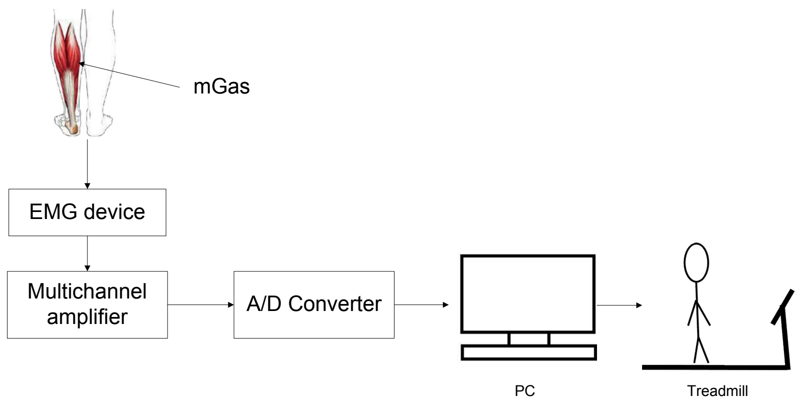

Figure 2. Experimental setup during surface EMG data recording. A/D: analog-to-digital; mGas: gastrocnemius medialis.

The EMG signals were sampled at a rate of 1000 Hz using the Cortex software. Before conducting the experiment, each of the subjects was instructed to walk bare-footed at a self-selected comfortable pace on the treadmill for 3 s at a constant speed of 3 km/h. After the initial warm-up, the subjects underwent the task of walking on the treadmill for 5 s with the same speed as earlier. The experimental protocol was approved by the local ethical committee. The raw EMG signals then went through a high-pass and a low-pass filter with the second-order Butterworth at 20 Hz and 500 Hz, respectively, to minimise interference and unwanted line frequencies (50/60 Hz). An example recording of mGas muscle during 5 s is depicted in Figure 3.

There were two main methods used for data windowing: adjacent and overlapping. As adjacent windowing techniques are widely adopted in the literature to analyse the stationarity of EMG signals [21,24–26], only adjacent windowing techniques were considered in this study. Adjacent windowing is where disjointed segments with a predefined length, S_i use feature extraction and classification after a certain processing delay, τ as shown in Figure 4. The τ is the processing time required to calculate the feature and classify the data. Adjacent windowing approach is commonly utilised to determine whether the EMG signals remain stationary or otherwise [21,24–26]. In this study, the data were divided into adjacent segments with the length of window size 100, 200, 500, and 1000 (ms).

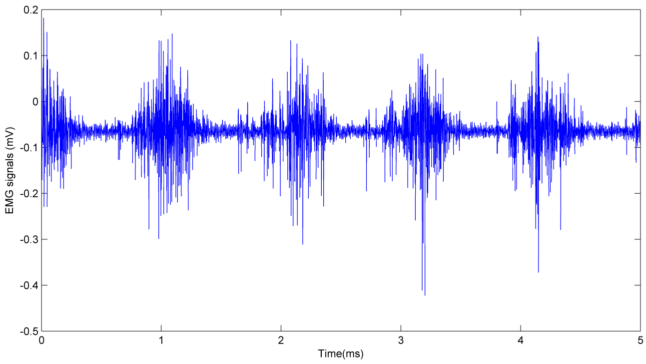

Figure 3. A sample of output data from EMG signals during walking on the treadmills for 5 s.

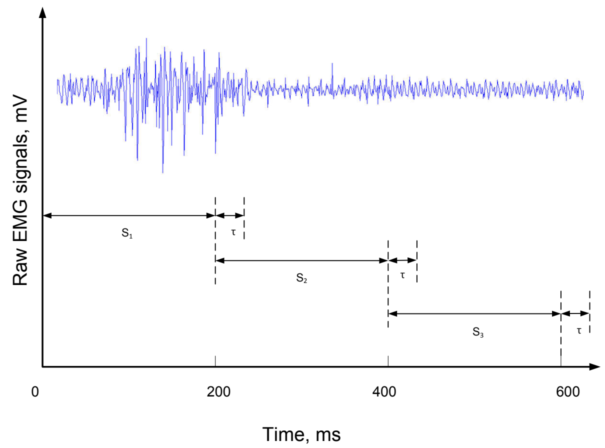

Figure 4. Adjacent windowing techniques.

2.2. Stationary Tests

Bendat and Piersol suggested that there are three types of non-stationary signals—namely, signals with a time-varying mean value, mean square value, and frequency structure [32]. There are various tests in the literature that can be applied to test the stationarity of EMG signals; for example, the run, reverse arrangement (RA), and modified reverse arrangement (MRA) tests [23]. Among the documented tests, RA and MRA were highly adopted [23,24]. According to Thongpanja et al., MRA test showed better performances than other tests for isometric contractions [26]. Nevertheless, this statement should be thoroughly examined for isotonic contractions cases. Therefore, this study considered both RA and MRA tests and further evaluated the performances of both tests.

The stationarity analysis was applied to the last 4 s, which was the first segment since the level of the excitatory drove over the initial 1 s was not sufficient to recruit all motor unit muscles [25]. The first segment was segmented into three window sizes including 100, 200, 500 and 1000 ms to test the local stationarity of each segment. For instance, there were four adjacent segments of 1000 ms. Consequently, the authors recorded 32 segments for one subject and 224 segments of EMG signals in total. Each of the 32 segments was divided into 10 equal adjacent sub-segments of duration *t* ms.

2.3. Reverse Arrangements Test

The RA test is performed by dividing the input signal into adjacent 100, 200, 500 and 1000 ms segments with 10 sub-segments and calculating the mean value $y_i(i = 1, 2, 3, \ldots, n)$ for each sub-segment. The number of reverse arrangements (A) in the sequence $y_1, y_2, y_3, ..., y_n$ are counted when $y_i > y_j$ for $i < j$. In other words, A is the number of times that the value of the first data point y_1 in the segment is higher than each subsequent data point value, $y_2, y_3, ..., y_n$. This process is then repeated for $y_2, y_3, ..., y_{n-1}$ [23]. A z-score can then be calculated using the following equation [32]:

$$z = \frac{A - [\frac{n(n-1)}{4}]}{\sqrt{\frac{n(2n+5)(n-1)}{72}}} \quad (1)$$

where A = total number of reverse arrangements in the EMG signals, and N = total number of data points. The null hypothesis for this test was that the mean value y_i in the signal are independent observations from a random variable. The alternative hypothesis was that the mean values y_i that make up the signal are related and are part of a significant trend underlying the signal. To reject the null hypothesis at $p \leq 0.05$ requires a z score of $z \geq 1.96$ or $z \leq -1.96$.

Modified Reverse Arrangements Test

Similar to the RA test, the MRA test was applied into adjacent 100, 200, 500, and 1000 ms segments with 10 sub-segments and the mean square value was calculated for each sub-segment. Theoretically, the mean square values from adjacent segments of a stationary signal are independent observations from a random variable. Thus, time trends in the mean square values may be due to a source of signal nonstationarity [32]. The test then requires the calculation of the number of times, A—beginning with the first mean square value y_1 in the sequence of 10 ms sub-segments y_i—that each subsequent mean square value $y_1, y_2, y_3, ..., y_n$ is less than y_1. This process was then repeated for $y_2, y_3, ..., y_{n-1}$. A z-score could then be calculated using the following equation:

$$z = \frac{A - [\frac{n(n-1)}{4}]}{\sqrt{\frac{n(2n+5)(n-1)}{72}}} \quad (2)$$

where A = total number of reverse arrangements in the EMG signals, and N = total number of data points. The null hypothesis for this test was that the mean values y_i in the signal were independent observations from a random variable. The alternative hypothesis was that the mean values y_i that make up the signal were related and part of a significant trend underlying the signal. To reject the null hypothesis at $p \leq 0.05$ requires a z score of $z \geq 1.96$ or $z \leq -1.96$.

Both tests were carried out utilising MATLAB software. By performing both tests, the EMG signals were then classified as stationary and non-stationary according to the z-score for each trial set. For each window size and subject, the percentage of the stationary signals was calculated using the following equation:

$$\text{Percentage of the stationary} = \frac{N_z}{N_t} \quad (3)$$

where N_z is the number of stationary segments with respect to a window size, N_t is the total number of segments with respect to window size, and i is the index of the EMG signals.

3. Results

Figure 5 illustrates the results from stationary tests for the first segment of EMG signals with 100, 200, 500, and 1000 ms window sizes. The red and blue curves representing the measured value, A, were obtained from RA and MRA tests, respectively. As observed, both red and blue curves laid between the upper and lower boundaries for 100 and 200 ms window sizes. Meanwhile, the curve of A was slightly outside the upper and lower boundaries for window sizes 500 and 1000 on both tests. Figure 6 presents the average percentage the stationary EMG signals for all subjects. If the threshold was set at 80% of stationary, a suitable window size should be 100 ms and 200 ms based on both tests. Using the RA test, the percentage of EMG signals determined to be stationary within 100 ms, 500 ms, and 1000 ms window sizes was recorded to be 88.21%, 50%, and 35.71%, respectively. The percentage of stationary EMG signals within 100 ms, 500 ms, and 1000 ms window sizes in the MRA test were 87.86%, 51.89%, and 39.29%, respectively. The 200 ms window size yielded similar results in both tests, with 88.57% being the highest value recorded.

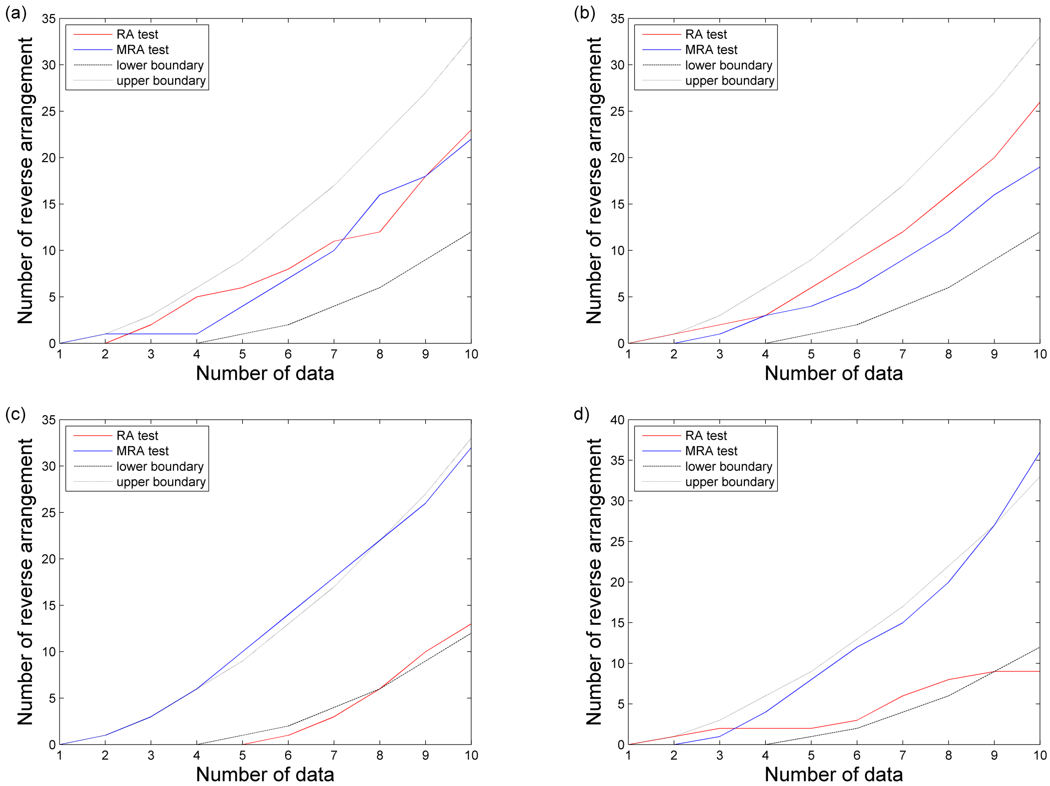

Figure 5. The result of stationarity tests with (**a**) 100 ms; (**b**) 200 ms; (**c**) 500 ms; and (**d**) 1000 ms window size. RA: reverse arrangement; MRA: modified reverse arrangement.

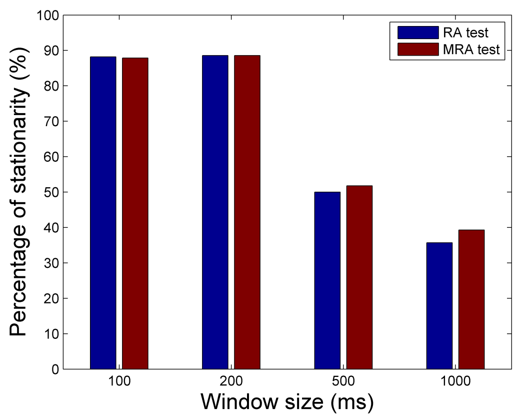

Figure 6. Average percentage of stationary EMG signals obtained from RA and MRA tests at various windows size conditions.

4. Discussion

Many researchers have endeavoured to satisfy the assumptions of stationarity in EMG signals in order to adopt TD features in pattern recognition. Stationarity tests were conducted to evaluate the data of EMG signals for various types of contractions. According to Bilodeau et al., the EMG signals recorded from upper limb during ramp and step isometric contractions are relatively stable, as there were no identifiable trends in the mean for 16 segments [21]. The researchers found that EMG signals were stationary in most cases—92.2% within 512 ms window size. As mentioned, the assessment of stationarity depends on the window size. Cho and Kim showed that the stationarity level of the EMG signals increase when the window size increases with a relatively low stationarity with window sizes of 250 and 500 ms in the RA test in their study [33]. Contrary to Thongpanja et al. [24], the stationarity increased only from 128 ms to 375 ms window size with an average 94.29%. Even though the peak of the EMG stationarity level was found at the 512-samples window depending on one subject, on average, there existed a small decrement and increment between 512 ms and 1024 ms window size. Meanwhile, the stationarity of EMG was at the highest with 250 ms window size and lowest at 1000 ms window size in the MRA test compared to 500 and 2000 ms [25]. Nonetheless, most of the available studies concentrated on isometric contraction.

During isotonic contraction, the EMG signal's stationarity can be affected by the location of an electrode, changes in muscle length, and muscle forces. It was reported that a suitable window size for isotonic contractions lies within the 125 ms window size range with approximately 90% stationarity [26]. However, if the threshold was set at 80% stationarity, a suitable window size was determined to be 250 ms or lesser. As a result, EMG signals in this study for the first sub-segment were stationary within 100 ms and 200 ms window sizes compared to 500 and 1000 ms, as the curve of the measured value (*A* laid between the upper and lower boundaries based on both RA and MRA tests). This proved that approximately 87–89% of EMG signals were stationary based on both tests. However, the highest percentage on average was gained by a 200 ms window size for both tests. It can be concluded that 200 ms is suitable to analyse EMG signals.

The comparison of suitable window size with previous literature on the different types of contractions and stationary tests is depicted in Table 1. Referring to Table 1, the performances of both RA and MRA in signal stationarity are still in the midst of an investigation. Therefore, this study compared the performances of RA and MRA tests for isotonic contraction. Based on Figure 6, there was little difference in 100 window size for both tests, but the same cannot be said for 500 and 1000 ms. There was a small decrement of percentage (0.35%) in MRA test for 100 ms, but a higher increment in the range of 1.8–3.6% was observed for window sizes 500 and 1000 ms. Contrary to the 200 ms window size, the percentages remained the same for both tests. Thus, it can be concluded that the MRA test showed better performance than the RA test, as stated by Thongpanja et al. [26]. Though the validity of the statement was true for 500 and 1000 ms window sizes, the same cannot be concluded for 100 ms window size.

The findings of this study affirmed the results reported by Ahmad and Chappel [34] that the performance of TD features in detecting the stages of contraction for upper limb movement is comparable to the classification methods of time-frequency features in isometric contraction [11]. The results of this study are also in line with the research done by Maged et al., as the analysis of TD features within 200 ms window size was the most appropriate technique for classifying the four ankle joint movements in comparison to 50, 100, 150, and 250 ms, with classification accuracy of 97.32% [35]. This is in agreement with the result in [7] that the classification accuracy was improved from 77% to over 90% for window size from 100 to 600 ms. In contrast with the result found in [20], a window size of 100 ms gained a classification accuracy greater than 90%. A similar percentage was obtained for walking gait event detection with 313 ms window size, as discovered in [31].

Decreasing the window size might improve the classification performance by a lower processing time, but some windows would process without containing the desired event, as mentioned by Richer et al. [8]. They also stated that if the window size increases, it may have a negative impact on the real-time processing, and results in a higher computational load. It was reported that increasing window size from 250 ms to 300 ms and upwards provides no more than 1% average improvement in classification accuracy for each step-wise increment of the window length for all participant cases in [36]. Instead of aiming for higher classification accuracy, this study proved that the stationarity of EMG signals was higher within 200 ms window size, which may enhance the real-time processing in near future. Hence, a window size of 200 ms is suggested due to a compromise between feature bias (in short window sizes) and real-time constraints and signal stationarity (in long window sizes), and can be used for isotonic contractions.

Table 1. Comparison of suitable window size with different types of contractions. RA: reverse arrangement; MRA: modified reverse arrangement.

Author	Type of Contractions	Window Size (ms)	Stationarity Tests
[25]	Isometric	250	Run, RA, and MRA
[26]	Isotonic	125	MRA
[26]	Isometric	372	MRA
This study	Isotonic	200	RA and MRA

Even though the windowing techniques in pattern recognition and prosthesis control are an overlapped segmentation, an adjacent segmentation is widely adopted in determining the stationarity of EMG signals [21,24–26]. It was reported there was no difference in classification accuracy in discriminating upper limb movements during isometric contractions [19]. Thus, the classification performance is assumed to be the same in isotonic conditions. Future work could explore this assumption, and the effect of overlapped and adjacent windowing techniques in the stationarity of EMG signals might be investigated.

5. Conclusions and Future Work

The primary results of this study and the hypothesis of EMG signal stationarity recorded from mGas muscle were accepted based on stationarity tests. It can be concluded that there existed a stationary segment in isotonic contractions for all window sizes. Based on the RA and MRA tests, EMG signals within the 100 ms, 500 ms, and 100 ms window sizes were outperformed by the 200 ms window size. As reported in [26], the EMG signal stationarity decreased as the length of window size increased for window sizes ranging between 125 and 1000 ms in isotonic contractions. In contrast to this study, EMG signal stationarity decreased as the length of window size increased only for window sizes greater than 200. The average percentage was slightly lower for window sizes less than 100 ms. The outcome affirmed that the analysis of EMG signals using TD features in 200 ms window size was reliable and applicable for isotonic contractions. Accordingly, EMG signal analysis for 200 ms and greater required careful interpretation due to non-stationarity, as observed in this study. To note, for prosthesis and orthotic applications, window sizes less than 300 ms are acceptable. Future studies should consider other window sizes such as 250 ms, as the performance of the MRA test had better results compared to RA tests for window sizes greater than and equal to 200. The discovery in this study contradicts the statement found in the literature [24] when analysing window sizes within the 100 ms range. To conclude, the stationarity of EMG signals was found acceptable for a 200 ms window size, and there were no differences in the average percentages of stationarity obtained from RA and MRA tests. Future works should compare the stationarity of EMG signals between 200 to 300 ms window size. Additionally, the effect of the type of windowing techniques has not been explored.

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