Prediction of Long-Term Elbow Flexion Force Intervals Based on the Informer Model and Electromyography

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Abstract: Accurate and long-term prediction of elbow flexion force can be used to recognize the intended movement and help wearable power-assisted robots to improve control performance. Our study aimed to find a proper relationship between electromyography and flexion force. However, the existing methods must incorporate biomechanical models to produce accurate and timely predictions of flexion force. Elbow flexion force is largely determined by the contractile properties of muscles, and the relationship between flexion force and the motor function of muscles has to be thoroughly analyzed. Therefore, based on the investigation on the contributions of different muscles to the flexion force, original electromyography signals were decomposed into non-linear and non-stationary parts. We selected the mean absolute value (MAV) of the non-linear part and the variance of the non-stationary part as inputs for an Informer prediction model that does not require detailed a priori knowledge of biomechanical models and is optimized for processing time sequences. Finally, a long-term flexion force probability interval is proposed. The proposed framework performs well in predicting long-term flexion force and outperforms other state-of-the-art models when compared to experimental results.

Keywords: electromyography; Informer; force prediction; long-term prediction; confidence intervals

1. Introduction

With greater attention being given to physical health, the elderly have an increasing need for upper limbs to perform highly flexible tasks [1]. At present, wearable assist robots are currently used in the field of limb rehabilitation [2,3]. Although, the devices currently used for rehabilitation have only a single control scheme that cannot be customized for individual patients. Many researchers have used a combination of human bio-sensor technology and wearable assist robot technology to develop rehabilitation control algorithms [4]. The accurate prediction of upper limb flexion force will be key to improving the control of wearable assist devices [5,6].

Flexion force prediction (FFP) can be regarded as a crucial input for robot control systems. At present, the flexion force can be obtained in the following ways [7]: (a) Manual muscle testing (MMT). (b) Invasive direct measurement (IDM). (c) Kinematics and dynamics based methods. Nevertheless, each of these methods suffers from high expense, low precision, and irreparable damage to the body. Electromyography (EMG) provides motion information by monitoring bioelectrical signals generated by muscle contraction, and can also be used as a bioelectrical control signal. By analyzing and processing an EMG signal, a pattern of upper limb movement pattern can be recognized, although it is tough to accurately predict the associated force. Therefore, the extraction of information from EMG signals for an accurate and timely prediction of elbow flexion force is a significant challenge. Control of a wearable assist robot can be realized by monitoring EMG signals.
generated by muscles of the elbow joint. Therefore, the EMG signal is an ideal signal for a human–computer interaction system [8].

There are the following two widely used approaches for assessing FFP: non-machine learning and machine learning. Non-machine learning mainly adopts the parametric model algorithms developed over the past few decades. F. Romero et al. [9] proposed different Hill-type based muscle dynamics models for estimating force and discussed how the most appropriate Hill-model depends on the specific task. However, this method relies on a phenomenological model. A muscle biomechanical model was presented in [10] to estimate the force using EMG, and the performance of the model was evaluated by the index of coefficient of determination ($R^2$) and mean absolute value (MAV). In [11], the authors estimated force by incorporating EMG information into a muscle-twitch model. Thomas et al. [12] presented a forward dynamic neuromusculoskeletal model to estimate and predict joint moments and muscle forces. Considering the randomness and variability of biological signals, it is difficult to develop an accurate model of activation of human muscle. Machine-learning-based FFP methods have become an effective tool for estimating forces. In [13], the authors adopted an artificial neural network for estimating the elbow flexion force from an EMG signal during isometric contraction. In [14], a generalized three domains fuzzy wavelet neural network (TDFWNN) algorithm was used to accurately estimate the force from an EMG signal without prior knowledge of the biomechanical model. In [15], taking the quadriceps femoris muscle as an example, the acceleration of the knee joint was estimated by using the long short-term memory (LSTM) neural network model. In [16], the Fuzzy Theory and Deep Learning model based on EMG signals was proposed to estimate the applied forces in robotic surgery.

All the above research has been conducted on estimating force from surface EMG signals with different accuracy, there is as yet no convincing method for long-term and accurately predicting force magnitude. The fundamental reason is that it is not reliable to use a certain deterministic number to describe the time series with random fluctuation characteristics. This issue motivated us to introduce a probability-guarantee confidence interval to more reasonably describe future variations in flexion force. Intending to accurately predict flexion force, we propose a confidence interval prediction method of elbow joint flexion force based on the Informer model using EMG signals. We firstly analyze the main contributions from muscle contraction by considering the feature of EMG signals and elbow anatomy. Our analysis employs a wavelet-transform decoupling algorithm to decompose EMG time series into non-linear and non-stationary parts, from which we extract important features. After predictions are obtained from these two parts, we calculate the confidence interval of the predicted flexion force. The main contributions and novelty of our study can be summarized as follows:

1. Based on the analysis of elbow anatomy and features of the EMG time series, the EMG time series is creatively decomposed into the non-stationary part and the non-linear part.
2. The novel Informer-based prediction model is used to predict two parts of EMG signals. The Informer model is very suitable for long sequence time-series forecasting and exhibits excellent performance in accuracy and real-time. To the best of our knowledge, this is the first application of this model to FFP.
3. The confidence interval is used to express the changes in the elbow flexion force. The confidence interval is shown to be more useful than the numerical prediction for judging body movement and wearable robot control.
4. Our experimental results show that the error in flexion force predicted by the Informer model is smaller and the correlation coefficient larger than those that can be obtained using related methods.

The rest of the paper is organized as follows. Section 2 contains the problem statement and preliminary description of the Informer model; Section 3 describes the signals’ acquisition and the details of our method; Section 4 represents experimental results and
comparisons with other methods; Section 5 contains the conclusion and suggestions for future research.

2. Problem Statement and Preliminary Description

2.1. Problem Statement

When muscles contract at non-isometric speed, muscle force is not only related to EMG signal strength but also related to joint motion angle, muscle shape, muscle fatigue degree, and other factors [17]. As mentioned in [18], elbow flexion force is positively correlated with the amplitude of the EMG signal. Therefore, acquired EMG signals may have specific significance for reflecting the activity state of elbow flexion force. Research shows that brachioradialis and biceps are thought to be major muscle contribution to flexion force [19,20]. Figure 1 depicts the schematic diagram of muscle distribution of the forearm.

Figure 1. Schematic diagram of muscle distribution of forearm. 1. Extensor Carpi Radialis Longus, 2. Flexor Digitorum, 3. Pronator Teres, 4. Extensor Digitorum Communis, 5. Palmaris Longus, 6. Extensor Carpi Ulnaris, 7. Flexor Pollicis Longus, 8. Extensor Pollicis Longus, 9. Brachioradialis, 10. Flexor Pollicis Longus, 11. Biceps, 12. Flexor Carpi Ulnaris, 13. Flexor Carpi Radialis. This figure is referenced by [14].

In this paper, we will use a deep learning algorithm to explore the relationship between EMG signal and flexion force. In reference [20], Luo et al. assumed that there exists a nonlinear time-invariant mapping between EMG signals and force for a short time duration that can be expressed by \( F(i) = \varphi(X) \). Nevertheless, this model ignores the influence of adjacent muscles and noise. Based on the analysis of Figure 1. We can see that the EMG signal produced by the muscle is interfered with by the neighboring muscles. Moreover, they are also susceptible to electronic devices and environmental noise [21]. Therefore, the EMG signal is a dynamically changing time series, which is coupled with nonlinear characteristics and non-stationary characteristics. We assumed that EMG follows the basic noisy model, which is defined as:

\[
S(i) = f(i) + \epsilon \times e(i)
\]

where \( S(i) \) is the actual EMG time series that is disturbed by noisy signal, \( f(i) \) is the original EMG time series, \( e(i) \) is the mean-zero temporally dependent non-stationary process that follows the Gaussian distribution, and \( \epsilon \) is the standard deviation of the noise factor.

2.2. Preliminary

In this paper, we will employ the Informer model, which is a long-term time series prediction model for efficiency optimization based on Transformer [22]. This framework abandoned the way of information extraction of Convolutional Neural Network (CNN)
and Recurrent Neural Network (RNN), and creatively proposed the attention mechanism, which overcomes the shortcomings of efficiency problems and defects in the transfer of RNN and CNN. Figure 2 presents the overall framework of the Transformer model. It mainly consists of the Encoder part and Decoder part. The encoder part is composed of multiple coding blocks and the decoder is composed of multiple decoding blocks. The difference between the two parts is that the decoder has an encoder-decoder Attention module. The two Attention modules are used to calculate the weight of the input and output, respectively.

![Figure 2. The overall framework of Transformer.](image)

The canonical self-attention mechanism is the core module of the Encoder part. The eigenvector \( Z \) can be obtained from the input data through the SA module, which is expressed as:

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d}} \right)V
\]

(2)

where the \( Q \in \mathbb{R}^{(L, Q \times d)}, K \in \mathbb{R}^{(L, K \times d)}, V \in \mathbb{R}^{(L, V \times d)} \) represents the query matrix, the key matrix, and the value matrix, respectively, and \( d \) represents the vector dimension.

The softmax function is a generalization of the logistic function that maps a length-\( p \) vector of real values to a length-\( K \) vector of values, which can be expressed as:

\[
P(y|x) = \frac{\exp(W_y \cdot x)}{\sum_{c=1}^{C} \exp(W_c \cdot x)}
\]

(3)

where \( W_y \) and \( x \) are column vectors.

After obtaining the eigenvector \( Z \), it will be sent to the next module of the encoder, which is the FFN. The activation function of the first layer is ReLU, the second layer is linear activation function, which can be expressed as:

\[
\text{FFN}(Z) = \text{max}(0, ZW_1 + b_1)W_2 + b_2
\]

(4)

3. Methodology

The pipeline of our method is illustrated in Figure 3. The framework consisted of four parts including the EMG acquisition part, signal processing part, feature extraction part, and flexion force prediction part. When the elbow joint performs isometric contraction, the original EMG signals were collected from the two major areas (brachioradialis and...
biceps) of the forearm and considered as the input signal of the flexion force prediction model. Firstly, we decompose the original EMG time sequence into the nonlinear series and the non-stationary series through a wavelet decoupling algorithm. Then, we calculate the variances of the non-stationary series to extract the stochastic feature and calculate the MAV of the nonlinear series to extract the nonlinear feature. After that, they were sent separately into the Informer model to predict the nonlinear feature. At last, we obtain the force prediction confidence interval results.

![Figure 3](image-url)  
**Figure 3.** The pipeline of our method.

### 3.1. Signal Acquisition

The EMG signal acquisition system is a double conduction muscle electrical module that consists of analog circuit acquisition and digital signal filter processing (maximum sampling frequency 1000 Hz). The integrated dual Bluetooth module sends the collected data to the Bluetooth port on the PC. An area without muscle activity was selected as a reference electrode and two EMG sensors were placed at each end of the biceps. The elbow flexion force is collected by the force sensor acquisition system. The flexion force is estimated while the elbow joint is performing isometric contraction. The acquisition system is illustrated in Figure 4. The acquisition circuit collects the muscle EMG signals of the human arm through channel 1 and channel 2, then the MCU is used for digital filtering, and the EMG signal is processed to obtain the power. The sensor uses ADI chip AD8221 as an EMG signal for adjustable amplification, the output size depends on the amount of selected muscle activity. It is easy to use the Arduino controller to detect muscle activity.

![Figure 4](image-url)  
**Figure 4.** Schematic of the acquisition circuit and experiment setup.
3.2. Decoupling Processing

Most of the original EMG signals are often suffered from different types of noises such as electrode motion (EM), muscle artifact (MA), and baseline wander (BW), which are composed of many different components. Overall, an EMG signal is a kind of time series coupled with nonlinear and non-stationary features, which would lead to the wrong interpretation and affect the reliability and accuracy of the muscle force prediction. Therefore, the decomposing of the non-stationary part from the signal could be properly regarded as the decoupling process of the EMG time series.

Discrete Wavelet Transform (DWT) is developed according to the requirement of time–frequency localization. It has the characteristics of self-adaptation and mathematical microscope and is especially suitable for the processing of non-stationary and nonlinear signals [23,24]. We employ the DWT algorithm to decompose the original EMG time series into nonlinear and non-stationary parts. The DWT decoupling algorithm consists of the following three parts: signal decomposition, threshold processing, and signal reconstruction. The original EMG time series is decomposed by DWT, which is represented by a low pass filter and a high pass filter to extract the approximation coefficients and detail coefficients, respectively. It is worth noting that, the level of DWT is 2 and daubechies 3 wavelet is selected in this paper. The scheme of wavelet decomposition is illustrated in Figure 5.

![Figure 5. The scheme of the wavelet decomposition.](image)

Part 1: signal decomposition. We firstly employ the DWT to decompose the original EMG time series into approximation coefficients \( A_i \) and details coefficients \( D_i \).

Part 2: Threshold decoupling. From Part 1, we can obtain the detail coefficients of each level, a soft threshold is adopted for detail coefficients to suppress the high-frequency part of the noise. In [25], the author proposes a set of threshold methods, which can be used to obtain the conclusion when the dimension approaches infinity for the joint distribution of multidimensional independent normal variables and the optimal threshold under the limitation of minimum and maximum estimates. We adopt the most commonly used threshold, which is defined as follows:

\[
\lambda = \sqrt{2 \log(N)}
\]  

where \( \lambda \) is the threshold value under the determined scale and \( N \) is the length of EMG time series.
To make the reconstructed signal have better smoothness and avoid the signal oscillation caused by the hard threshold function, the soft threshold function is adopted in this paper. The threshold function is a soft threshold function that is shown as follows:

\[ \omega_T = \begin{cases} \text{sgn}(\omega)(|\omega| - \lambda) & |\omega| \geq \lambda \\ 0 & |\omega| < \lambda \end{cases} \]  

where \( \omega \) is the wavelet coefficient of the original EMG signal in the second layer of the wavelet decomposition.

Part 3: Signal reconstruction. The wavelet coefficients are used to reconstruct the decoupling EMG signal, which is taken as the non-linear series and denoted as \( f(i) \). The non-stationary series can be obtained by \( e(i) = S(i) - f(i) \).

3.3. Feature Extraction and Windowing

We can obtain the nonlinear part and non-stationary part of the original EMG time series after we use the DWT algorithm in Section 3.2. It is not appropriate to input two parts directly into the prediction model. Therefore, the purpose of this section is to extract the feature of nonlinear time series and non-stationary time series.

The analysis methods of time series are usually divided into frequency domain feature-based, time domain feature-based, and time–frequency domain feature-based. Considering the computation complexity and the redundancy of data information, we adopt the variance feature to represent the feature of non-stationary series according to its characteristics, which can be described as follows: Based on Equation (1), we firstly let \( e = \{ e(1), e(2), \ldots, e(i) \} \) represent the non-stationary series and calculate the mean of non-stationary series, which is expressed by \( \delta(j) \), \( j = 1, 2, \ldots, i - W + 1 \).

\[ \delta(j) = \frac{1}{W} \sum_{n=0}^{w-1} e(j + n) \]  

where the \( W (1 \leq W \leq 20) \) represents the moving window size that is determined empirically.

Then, the \( j \)-th variance time series of non-stationary series can be expressed as follows:

\[ V(j) = \frac{1}{W} \sum_{n=0}^{W} [e(j + n) - \delta(j)]^2 \]  

The variance of non-stationary series expressed as follows:

\[ V = \{ V(1), V(2), \ldots, V(j) \} \]

Most studies have shown that the mean average value (MAV) can be used as the most effective indicator of the signal characteristics [26]. Consequently, we adopt the MAV to extract the feature of the non-linear series. The equation of the MAV can be described as follows:

\[ MAV(i) = \frac{1}{N} \sum_{k=1}^{N} |x_k|, \text{ for } k = 1, \ldots, N \]  

The MAV of non-linear series is expressed as follows:

\[ MAV = \{ MAV(1), MAV(2), \ldots, MAV(i) \} \]

Deep learning-based algorithms often use rolling time series to achieve prediction [27]. The training set is divided into input–output pairs one by one, and the error between the output and the target real value is reduced by SGD iteration. In the prediction stage, the historical data of the previous period of the predicted data is used as the input to obtain the
predicted output. The rolling time series segment of MAV and V by slide window method is generated by the following:

\[
\begin{align*}
\text{MAV}_k &= \{\text{MAV}(i - W + 1), \text{MAV}(i - W + 2), \ldots, \text{MAV}(i)\} \\
V_k &= \{V(i - W + 1), V(i - W + 2), \ldots, x(i)\}
\end{align*}
\]

(10)

where \( W \) is the slide window size, \( \Delta t \) is time step, \( i = W, W + \Delta t, W + 2\Delta t, \ldots \).

3.4. Informer Prediction Model

The architecture of the Informer prediction model is shown in Figure 6. The Informer model to overcome the shortcomings of Transformer in long input/output series, complexity [28]. This study uses the Informer model to predict the non-linear series and the variance of the non-stationary series, respectively. For the non-stationary part, the input is the variance of the non-stationary series, the output is the predicted result of the variance series. For the non-linear part, the input is the MAV of the non-linear series, MAV, the output is the predicted result of flexion force time series. The length of input can be set according to the output requirements. The first 100 points of the sequence to be predicted are selected as a token.

**Figure 6.** The overall architecture of the Informer time series prediction model.

The process of the Informer model consists of the following steps:

1) Efficient Self-Attention Mechanism We calculate the weighted value of the \( i \)-th query and rewrite the Attention\((Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V\) into the following probability formulation:

\[
\text{Attention}(q_i, K, V) = \sum_j \frac{k(q_i, k_j)}{\sum_{j} k(q_i, k_j)} V_j = \mathbb{E}_{p(k_i|q_i)}[v_j]
\]

(11)

where \( p(k_i|q_i) = \frac{k(q_i, k_i)}{\sum_{j} k(q_i, k_j)}, k(q_i, k_i) = \exp\left(\frac{q_i k_i^T}{\sqrt{d}}\right) \), \( q_i \) and \( k_i \) represent the \( i \)-th row of matrix \( Q \), \( K \), and \( V \), respectively.

2) Query Sparsity Measurement To evaluate the sparsity of the \( i \)-th query, the relative entropy between the attention probability distribution of the query and the uniform
probability distribution was calculated by using the KL divergence. The KL divergence is calculated as follows:

$$KL(q||p) = \ln \sum_{j=1}^{L_K} e^{q_{kj}^T} - \frac{1}{L_K} \sum_{j=1}^{L_K} q_{kj}^T - \ln L_K$$ (12)

Due to the \(\ln L_K\) is constant, it does not affect the derivation of the following equation. Therefore, the \(i\)-th query’s sparsity measurement equation can be described as follows (13):

$$M(q_i, K) = \ln \sum_{j=1}^{L_K} e^{q_{kj}^T} - \frac{1}{L_K} \sum_{j=1}^{L_K} q_{kj}^T$$ (13)

where the first term on the left side is the Log-Sum-Exp (LSE) of \(q_i\) and the second term is the arithmetic mean. Replace \(\ln \sum_{j=1}^{L_K} e^{q_{kj}^T}\) with \(\max_j\{q_{kj}^T\}\), the maximum mean measurement is as follows:

$$\mathcal{M}(q_i, K) = \max_j\{q_{kj}^T\} - \frac{1}{L_K} \sum_{j=1}^{L_K} \sqrt{d}$$ (14)

3) ProbSparse Self-Attention Based on the above evaluation equations from (12)–(14), the following ProbSparse Self-Attention matrix can be obtained:

$$Attention(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_{key}}})V$$ (15)

where the \(\mathcal{Q}\) is a sparse matrix of the same size as \(q_i\).

4) Encoder The main function of the encoder part is to extract the interdependence between the long-time sequences. The distilling operation is used to give higher weights to the dominant features and generate a focus Self-Attention feature map at the next level. The distilling procedure forwards from \(j\)-th layer into \((j + 1)\)-th layer as follows:

$$X_{j+1} = \text{MaxPool} (\text{ELU} (\text{Conv}_1d([X_j^T]_{AB})))$$ (16)

where \([\cdot]_{AB}\) represents the Multi-head ProbSparse Self-Attention and the essential operations and \(\text{Conv}_1d(\cdot)\) represents 1-D convolutional filters on time dimension with the ELU activation function.

5) Decoder This part consists of two identical multi-attention layers. We input to the decoder with the following vectors:

$$X(de) = \text{Concat}(X(token), X(0)) \in \mathbb{R}^{(L_{token}+L_y) \times d_{model}}$$ (17)

where the \(X(token) \in \mathbb{R}^{L_{token} \times d_{model}}\) is the start token that is a segment that precedes the output sequence and \(X(0) \in \mathbb{R}^{L_y \times d_{model}}\) is a placeholder for the target sequence that sets scalar as 0.

3.5. Force Prediction Confidence Interval

Confidence interval is an estimated interval of population parameters constructed from sample statistics [29]. It shows the degree to which the actual force has a certain probability of falling around the predicted force. We could obtain the output results of flexion force \(F_e(k + 1)\) and variance \(V(k + 1)\) from the Informer model, respectively. The confidence interval of the flexion force prediction in this paper is calculated based on the prediction results of \(F_e(k + 1)\) and \(V(k + 1)\). Since the non-stationary part is considered as
the noise part of the EMG signal and is regarded as the Gaussian distribution. Therefore, the probability-guaranteed confidence interval of flexion force could be described as follows:

$$[F_e(k+1) - Z_{1-\alpha} \sqrt{V(k+1)}, F_e(k+1) + Z_{1-\alpha} \sqrt{V(k+1)}]$$  (18)

where $F_e(k+1)$ and $V(k+1)$ denote the predicted results of flexion force and variance at time step $k+1$, respectively. $Z_{1-\alpha}$ denotes the quantile of $1-\alpha$ of the standard Gaussian distribution and $\alpha$ denotes the confidence level.

3.6. Evaluation

The Normalized Root Mean Square Error (NRMSE) and coefficient of determination ($R^2$) are taken into account to evaluate the performance of our algorithm [30]. NRMSE is often used as a tool to evaluate the similarity between the measured value and the actual value. When the ratio value is low, it represents less residual variation. $R^2$ is a statistic to measure the degree of fitting in multiple regression equations. The closer $R^2$ is to 1, the greater the proportion of the regression sum of squares to the total sum of squares and the better the fitting degree of the prediction results. Generally speaking, a better prediction model has better evaluation indicators (NRMSE close to 0, $R^2$ close to 1).

$$\text{NRMSE}(F_e, F_t) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (F_t - F_e)^2 / (F_{\max} - F_{\min})}, \quad i = 1, 2, \ldots, n$$  (19)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (F_t - F_e)^2}{\sum_{i=1}^{n} (F_t - \overline{F_t})^2}, \quad i = 1, 2, \ldots, n$$  (20)

where $F_t$ represents the actual force measured from the force sensor, $F_e$ represents prediction force, $F_{\max}$ represents the maximum of the actual force, $F_{\min}$ represents the minimum of the actual force, and $\overline{F_t}$ represents the mean value of actual force.

4. Experimental

We selected five healthy subjects (24 ± 3 years, without musculoskeletal diseases) for the study. All the subjects were given adequate information about the purpose and procedure of the study. To collect accurate and effective EMG signals, the subjects did not exercise vigorously before the collection experiment, keeping the muscles naturally relaxed. To ensure the effectiveness of EMG signals, subjects did not perform strenuous exercise before each experiment and kept the upper limb muscles naturally relaxed to avoid the influence of muscle fatigue on EMG signals. The subjects have 10 s rest before every trial.

In this study, they were asked to perform isometric contraction, the main feature is that the muscle fiber is not changed and there is no contraction movement occurring during the contraction period. The isometric task is usually used as the research object of force prediction. We designed four specific isometric contraction tasks. They were required to shrink from 0 to 100% maximum voluntary contraction (MVC) three times within 1, 2, and 3 s, respectively.

4.1. Decomposition of EMG

A total of 30,000 sets of data were collected in the experiment. We used the DWT algorithm for decoupling processing and intercepted 2000 sets of data. We collected the original EMG signals of three contraction modes (1, 2, and 3 s) at different angle and used the DWT algorithm for decomposition. The detail of the process is depicted in Figures 7–9.
Figure 7. In the case of 1 s contraction: (a) Original EMG series, (b) Nonlinear series, (c) Non-stationary series, (d) Variance of Non-stationary series.

Figure 8. In the case of 2 s contraction: (a) Original EMG series, (b) Nonlinear series, (c) Non-stationary series, (d) Variance of Non-stationary series.
4.2. Flexion Force Prediction Results

We divide the non-linear series and non-stationary series into training part and testing part with a ratio of 8:2 to verify the performance of the model. We calculate the upper boundary and lower boundary of the tested EMG when $a = 0.95$. Moreover, the shorter window size would reduce the computational efficiency and the longer window would reduce the accuracy. Therefore, we must dynamically balance efficiency and precision. Table 1 summarizes the prediction accuracy of the network under different moving window sizes. $W = 20$ is more suitable in this experiment.

Table 1. Evaluation index ($\text{NRMSE}$ and $R^2$) of our algorithm for different window sizes $W$.

| Index | $W = 5$  | $W = 15$ | $W = 20$ | $W = 25$ | $W = 15$ | $W = 35$ |
|-------|----------|----------|----------|----------|----------|----------|
| NRMSE | 1.3N     | 1.1N     | 1.3N     | 2.2N     | 2.5N     | 4.1N     |
| $R^2$ | 0.91     | 0.95     | 0.96     | 0.94     | 0.82     | 0.90     |

Figure 10 shows the result of flexion force prediction using our algorithm. Figure 10a–c is the original EMG signal under 1, 2, and 3 s contraction mode, respectively. Figure 10d–f is the decoupled signal processed by the DWT algorithm. Figure 10g–i is the prediction confidence interval of flexion force based on the Informer model. The red solid line is the
actual force, the blue solid is the predicted results. Based on the analysis of the experimental statistical results, 95 actual values fall within the prediction interval in Figure 10g, 96 actual values fall within the prediction interval in Figure 10h, and 94 actual values fall within the prediction interval in Figure 10i. The experimental results show that the proportion between the actual results and the predicted results is consistent with the confidence level of 0.95. Therefore, we can obtain the following conclusions: The proposed FFP algorithm based on the Informer model can produce an accurate confidence interval that can be used as reliable results.

![Figure 10](image_url)

**Figure 10.** Prediction results under different contraction modes. (a–c) is original EMG during three contraction mode (1 s, 2 s, 3 s); (d–f) is nonlinear series after using DWT algorithm during three contraction mode (1 s, 2 s, 3 s); (g–i) is force prediction result during three contraction mode (1 s, 2 s, 3 s).

### 4.3. Comparison and Discussion

We compare the Informer (confidence level $\alpha = 0.95$) prediction results with other state-of-art algorithms including the LSTM, Transformer, and Prophet algorithms. We select one subject (age is 26, the fixed angle is 90°) to collect 3000 raw EMG signals of biceps. We zoom in on the comparative results, as shown in Figure 11. From the figure, it can be known that (1) the results of the flexion force prediction based on Prophet, LSTM, and Transformer predict the exact value of flexion force, however, the reliability of the prediction results will decrease when the disturbance is large. (2) Our method can provide accurate confidence intervals results, the prediction results of other mainstream algorithms are almost in the prediction intervals.

To verify the effectiveness of the proposed algorithm from multiple perspectives. We validated different subjects under the same contraction mode and the same subjects under different contraction modes. Figure 12a,c shows the coefficient of determination and NRMSE results of different subjects. Figure 12b,d shows the coefficient of determination and NRMSE result of different angles (30°, 60°, 90°, 120°). It can be known that (1) although there are differences among different individuals, the algorithm proposed in this study obtains the highest coefficient of determination and the lowest NRMSE compared with other algorithms. (2) When the angle is at 120°, the prediction performance of all the algorithms is the best among other angles. The reason is that the measured muscle is least
interfered with by other adjacent muscles that can effectively represent the variation of flexion force.

![Confidence Interval](image)

**Figure 11.** Comparative study of the different prediction algorithms (The confidence level $\alpha = 0.95$ in this experiment).

![Performance Comparison](image)

**Figure 12.** The performance comparison of different algorithm. (a) The coefficient of determination comparison of different algorithms in different subjects. (b) The coefficient of determination comparison of different algorithms in different angles. (c) The NRMSE comparison of different algorithms in different subjects. (d) The NRMSE comparison of different algorithms in different angles.
Figure 13 shows the $R^2$ and NRMSE evaluation results under different prediction lengths (100, 500, 1000). We found that with the increase in the prediction length, the accuracy of all prediction algorithms would decrease. When the prediction length exceeds 100 points, the prediction performance of other models decreases rapidly except for the Informer model. Therefore, the Informer model is more suitable for long-term flexion force prediction.

![Figure 13](image_url)

**Figure 13.** Comparison of the evaluation index of different algorithms in different prediction lengths. (a) The comparison results of $R^2$ index. (b) The comparison results of NRMSE index.

5. Application and Limitation

The results of flexion force prediction could provide more effective guidance information for the control of assistance robots in the human–machine interaction field. The flow chart is shown in Figure 14.

![Figure 14](image_url)

**Figure 14.** The application example of FFP in human–machine interaction. Based on the judgment of motion intention and the prediction of flexion force, they can be used as effective input signals of the power-assisted robot system to realize the compliant control of upper limb movement.

The main drawbacks of this research are as follows: (1) Only the isometric contraction task was considered, other contraction tasks need to be validated. (2) Only EMG signal was used as input for algorithm verification, other biological signals such as MMG, ECG, should be taken into consideration.

6. Conclusions

In this paper, we present an elbow flexion force prediction confidence interval method based on the Informer model. The proposed framework consists of three parts, the first
part is based on the analysis of characteristics of the EMG signal to decompose the EMG signal into the non-stationary series and the non-linear series using DWT. The second part is accomplished by using the Informer model to predict the nonlinear part and the variance of the non-stationary part, respectively. The third part is based on the confidence interval idea to calculate the long-term prediction of elbow flexion force interval. The experiments demonstrate the effectiveness of the algorithm from three aspects. Through the comparison results, the prediction method proposed is more accurate in predicting the flexion force. The best prediction results of our model can satisfy $R^2 = 0.998$ and NRMSE = 0.05.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data used to support the findings of this study are included within the article.

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References

1. Lencioni, T.; Fornia, L.; Bowman, T. A randomized controlled trial on the effects induced by robot-assisted and usual-care rehabilitation on upper limb muscle synergies in post-stroke subjects. *Sci. Rep.* 2021, 11, 5323. [CrossRef]
2. Lotti, N.; Xiloyannis, M.; Durandau, G. Adaptive model-based myoelectric control for a soft wearable arm exosuit: A new generation of wearable robot control. *IEEE Robot. Autom. Mag.* 2020, 27, 43–53. [CrossRef]
3. Tortora, S.; Michieletto, S.; Stival, F. Fast human motion prediction for human-robot collaboration with wearable interfaces. In Proceedings of the 2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), Bangkok, Thailand, 18–20 November 2019.
4. Tang, D. Design and Analysis of the Wearable Power Assisted Robot. *Recent Pat. Eng.* 2018, 12, 230–236. [CrossRef]
5. Du, Y.; Wang, H.; Qiu, S. An Advanced Adaptive Control of Lower Limb Rehabilitation Robot. *Front. Robot. AI* 2018, 5, 116. [CrossRef]
6. Li, X.; Zhong, J. Upper Limb Rehabilitation Robot System Based on Internet of Things Remote Control. *IEEE Access* 2020, 8, 154461–154470. [CrossRef]
7. Wang, J.; Pang, M.; Yu, P. Effect of Muscle Fatigue on Surface Electromyography-Based Hand Grasp Force Estimation. *Appl. Biomech.* 2021, 2021, 8817480. [CrossRef] [PubMed]
8. Gui, K.; Liu, H.H.; Zhang, D.G. A Practical and adaptive method to achieve EMG-based torque estimation for a robotic exoskeleton. *IEEE-ASME Trans. Mechatron.* 2019, 24, 483–494. [CrossRef]
9. Romero, F.; Alonso, FJ. A comparison among different Hill-type contraction dynamics formulations for muscle force estimation. *Mech. Sci.* 2016, 7, 19–29. [CrossRef]
10. Na, Y.; Choi, C.; Lee, H.D.; Kim, J.K. A study on estimation of joint force through isometric index finger abduction with the help of seng peaks for biomedical applications. *IEEE Trans. Cybern.* 2016, 46, 2–8. [CrossRef]
11. Na, Y.; Kim, S.J.; Kim, J. Force estimation in fatigue condition using a muscle-twitch model during isometric finger contraction. *Med. Eng. Phys.* 2017, 50, 103–108. [CrossRef] [PubMed]
12. Buchanan, T.S.; Lloyd, D.G.; Manal, K. Estimation of muscle forces and joint moments using a forward-inverse dynamics model. *Med. Sci. Sports Exerc.* 2005, 37, 1911–1916. [CrossRef] [PubMed]
13. Youn, W.L.; Kim, J. Estimation of elbow flexion force during isometric muscle contraction from mechano-myography and electromyography. *Med. Biol. Eng. Comput.* 2010, 48, 1149–1157. [CrossRef]
14. Luo, J.; Liu, C.; Yang, C. Estimation of EMG-Based Force Using a Neural-Network-Based Approach. *IEEE Access* 2019, 7, 64856–64865. [CrossRef]

15. Xie, C.; Wang, D.; Wu, H. A long short-term memory neural network model for knee joint acceleration estimation using mechanomyography signals. *Int. J. Adv. Robot. Syst.* 2020, 17, 172988142096870. [CrossRef]

16. Aviles, A.I.; Alsaleh, S.M.; Montseny, E. A Deep-Neuro-Fuzzy approach for estimating the interaction forces in Robotic surgery. In Proceedings of the 2016 IEEE International Conference on Fuzzy Systems, Vancouver, BC, Canada, 24–29 July 2016.

17. Oboe, R.; Tonin, A.; Yu, K. Weight estimation system using surface EMG armband. In Proceedings of the IEEE International Conference on Industrial Technology, Toronto, ON, Canada, 22–25 March 2017.

18. Kamineni, S.; Ashfaq, H.; Alluri, S. Radial Nerve Anatomy at the Elbow Joint and Its Arthroscopic Relevance. *Arthrosc. J. Arthrosc. Relat. Surg.* 2019, 35, e32. [CrossRef]

19. Staudenmann, D.; Kingma, I.; Daffertshofer, A. Improving EMG-based muscle force estimation by using a high-density EMG grid and principal component analysis. *IEEE Trans. Biomed. Eng.* 2006, 53, 712–719. [CrossRef]

20. Zonnino, A.; Sergi, F. Model-based estimation of individual muscle force based on measurements of muscle activity in forearm muscles during isometric tasks. *IEEE Trans. Biomed. Eng.* 2019, 67, 134–145. [CrossRef]

21. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, J.; Gomez, A.G.; Kaiser, L.; Polosukhin, I. Attention Is All You Need. In Proceedings of the 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA, 4–9 December 2017; pp. 6000–6010.

22. Peng, Z.K.; Chu, F.L. Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography. *Mech. Syst. Signal Process.* 2004, 18, 199–221. [CrossRef]

23. Liu, X.; Liu, H.; Guo, Q. Adaptive wavelet transform model for time series data prediction. *Soft Comput.* 2020, 24, 5877–5884. [CrossRef]

24. Chao, W.; Ni, Z.; Zhang, J. Induced and transferred charge signals decoupling based on discrete wavelet transform for dilute gas-solid two-phase flow measurement. In Proceedings of the IEEE International Instrumentation & Measurement Technology Conference, Turin, Italy, 22–25 May 2017.

25. Wang, D.; Xie, C.; Wu, H. Estimation of Knee Extension Force Using Mechanomyography Signals Detected Through Clothing. In *International Conference on Intelligent Robotics and Applications*; Springer: Cham, Switzerland, 2019.

26. Zhang, J.; Wu, Z.C.; Li, F. A Deep Learning Framework for Driving Behavior Identification on In-Vehicle CAN-BUS Sensor Data. *Sensors* 2019, 19, 1356. [CrossRef]

27. Guo, L.; Li, R.; Jiang, B. A Data-Driven Long Time-Series Electrical Line Trip Fault Prediction Method Using an Improved Stacked-Informer Network. *Sensors* 2021, 21, 4466. [CrossRef] [PubMed]

28. Garland, I. Using the Past to Predict the Present: Confidence Intervals for Regression Equations in Phylogenetic Comparative Methods. *Am. Nat.* 2000, 155, 346. [CrossRef] [PubMed]

29. Staudenmann, D.; Roeleveld, K.; Stegeman, D.F. Methodological aspects of SEMG recordings for force estimation—A tutorial and review. *J. Electromyogr. Kinesiol.* 2010, 20, 375–387. [CrossRef] [PubMed]