The Classification and Objective Measure of Strength of an Exercise via Analysis of Electromygraphy

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***Abstract*— In recent years, telehealth and telerehabilitation have been on the rise due to lock down and quarantine placing restrictions on in-person healthcare during the 2020 Covid Pandemic. However, there are some limitations to the service that physicians are able to do it remotely. This paper proposes a contemporary way of collecting more data from the remote patient to help during their telerehabilitation appointments. Surface electrodes are placed on the participants' forearm flexor muscles and samples were collected for each exercise. The data were then analyzed and the features, RMS, IEMG, and VAR were used. The exertion of the strength of the muscle during an exercise could be seen from plotting the RMS of the exercise to the IEMG time domain graph, and the classification of the exercise could be interpreted from the IEMG data from one exercise, that has been normalized, which was plotted as a box plot diagram to be compared with the other exercises. The findings from this paper could be used in helping to build a model to ensure that the exercises are done correctly and the muscles are not being strained too hard during an exercise by the physician during a telerehabilitation session.**

Keywords— telerehabilitation, integrated electromyography, surface electrode, strength classification, flexor carpi ulnaris, extensor digitorum

I. INTRODUCTION

Over the past century, electromyography (EMG) has been a popular tool to aid in research regarding the motor units [1] in our limbs and joints. Generally, the EMG signal is obtained via a surface electrode placed on the targeted muscle group that contracts during the experiment. These contractions allow the researcher to detect the magnitude of a muscle force [2] which could result in further muscle movement in adjacent muscles [3] and cause muscle fatigue and strain [4].

Previous research in electromyography has mostly consisted of investigating the targeted motor unit's properties [1] and how pain could be induced by repetitive motions of the muscle which could halt an athlete's or performance artist's [5]. Furthermore, there have been studies on animals concerning how the EMG signals of muscles affected by neurodegenerative diseases, such as Amyotrophic lateral sclerosis (ALS) [6] or denervated muscles in frog legs that resemble atrophied and dystrophic human muscles [7].

Additionally, in 2008, Roberts, Thomas J., and Annette M. Gabaldón wanted to find out if there was any correlation between muscle function and the muscle force measured by the EMG electrodes [2]. Probe sensors for the EMG were used to access the muscle fibers in the turkey's leg. The turkey was screened to ensure it had no health conditions and trained to run on a treadmill (Keys Pros 2000) at a range of speeds for 20 minutes for 4-5 sessions per week in 6 - 10 weeks. After the training period was over, a fine wire and bipolar EMG electrodes were surgically implanted into the turkey and the turkeys were put on a treadmill to run from speeds of 1 ms^{-2} to 4 ms^{-2} at ±6 and ±12 inclines. 10 strides were analyzed from each running trial and a mean r-EMD and velocity were found. The results found no correlation between the speed of the turkey and the r-EMD.

Moreover, in 1992 researchers Sundelin, Gunevvi and Mats Hagberg set out to find signs of muscle fatigue in the shoulder muscle due to repetitive motion [8]. The participants were asked to perform a repetitive task of grabbing a cylinder using only their right arm from a box 40 cm away and putting it into a hole in the center of the desk. The task was broken down into 4 main components: reaching, grasping, moving and releasing the object. The subjects repeated the task for 1 hour and then their maximal elevation strength and external rotation strength of their right shoulder were measured via a strain gauge dynamometer and their EMG activity was recorded using surface electrodes. Results found a lot of variation between shoulder muscle load and static load during the whole work period and clear indicators of muscle fatigue as seen by the regression lines plotted out. Additionally, during the five-minute periods, there were also signs of muscle fatigue however they were not consistent between subjects.

However, there are other applications for EMGs aside from just measuring muscle force for research. In recent years, telerehabilitation has exploded onto the new age scene. Telerehabilitation is an online therapy service that aims to provide physical therapy to patients remotely via a video call between the patient and the physician. One benefit of telerehabilitation could be allowing patients to consult with a physician even if they don't have access to a clinic or hospital due to time constraints or geographical reasons. Additionally, during the COVID-19 pandemic, the demand for telerehabilitation increased exponentially as it allowed the physician or the patient to attend the consultation while sick with a contagious virus (as long as they feel well enough).

Nevertheless, using online video calls indicates a glaring issue with telerehabilitation; the physician may be unable to determine if a patient is doing the exercises correctly or is doing the exercise with the appropriate amount of strength from just vision alone. This is where electromyography comes in. Using surface electrodes on the patient, the physician can obtain quantifiable data about the exercise. This study aims to analyze data that could be acquired from the exercise through surface electromyography (sEMG) signals from patients to determine what specific muscles are being used during an exercise and check if the exercise is being done correctly. In this paper, we will cover the instruments used in this experiment (surface electrodes and microcontrollers), the procedure used to obtain the data from participants, an analysis of the results from the data and an overall conclusion of the experiment.

II. PRINCIPLE

This section of the research paper is composed of a discussion of the instruments that have been used to measure the EMG data from the participants and the instruments used to help process the data to obtain the result of the research.

A. *Electrode*

Multiple methods exist for capturing EMG signals. However, this research paper uses surface electromyography (sEMG): surface electrodes will be placed on the skin over the muscle of interest, in this instance, the Carpi Ulnaris muscles. This method is chosen because the sEMG is non-invasive and widely used in clinical and research settings[9]. Fig. 1. shows the component of the electrode. The snap connector is a metallic component on the top of the electrode, allowing for easy attachment and detachment of the lead wires connecting the electrode to the EMG amplifier which will provide a secure and stable connection, ensuring that the electrical signals detected by the electrode are reliably transmitted to the recording device[9]. The metal disk or the sensing surface is made from silver chloride which detects the electrical potential generated by muscle during muscle contraction[10]. The gel often contains an electrolyte which helps to maintain good electrical contact between the skin and the metal disk[11].

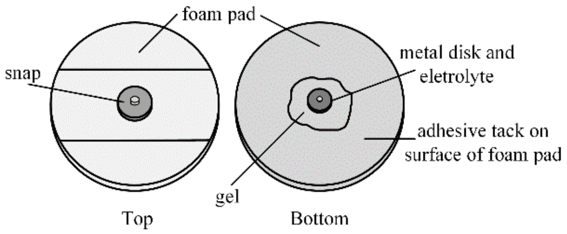


Fig. 1. Electrode.

B. *Amplifying Circuit*

The maximum voltage output directly from the EMG electrode, when muscle contracts the EMG signal is typically very low, often less than 50 mV, due to the minimal magnitude of the threshold voltage. Therefore, an instrumentation amplifier is used to amplify the voltage of the output signal from the EMG electrode. As a differential amplifier, the instrumentation amplifier is optimal for amplifying small-magnitude signals, as its gain will be larger for non-noise signals. Fig. 2 displays the schematic of the instrumentation amplifier, while (1) expresses the circuit's gain. The V_{output} will have a range between 0-5V.

$$Gain = \left(1+\frac{2R_1}{R_G}\right)\frac{R_3}{R_2} \qquad (1)$$

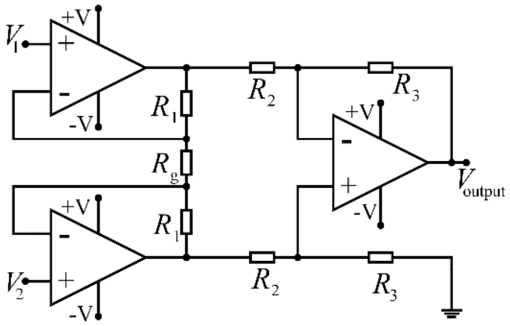


Fig. 2. instrumentation amplifier.

C. *Filters*

Filters are used to remove noise and interference to reduce background noise. Commonly used filters include high-pass filters to remove low-frequency noise and low-pass filters to eliminate high-frequency interference [12]. Raw EMG signals contain various types of noise, making it necessary to use a filter to isolate the relevant muscle activity signals. This paper will use a bandpass filter. A band-pass filter is an electronic filter that allows signals within a specific frequency range to pass through, in this instance 20Hz - 500Hz. The frequency response bandpass is shown in fig. 3.

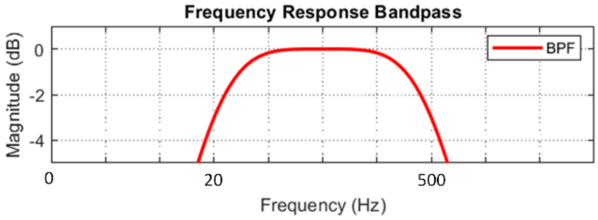


Fig. 3. frequency response bandpass filter.

D. *ADC Analog-to-digital converter*

An Analog-to-Digital Converter (ADC) is an electronic device that converts continuous analogue signals into discrete digital numbers. The ADC samples the analogue signal at specific intervals and converts each sample into a digital value that represents the amplitude of the signal at that point in time. In Nyquist Theorem, an analogue signal must be sampled at a rate that is at least twice the highest frequency component in the signal for an ADC to accurately capture it. In other words, signals can only be successfully digitized if their highest frequency components are less than half of the sampling frequency.

In this paper, the Arduino Mega 2560 microcontroller is used to convert analogue EMG signals to digital. The Arduino Mega 2560's ADCs have a resolution of 10 bits, in other words, the Arduino Mega 2560 is capable of quantizing at a 2^{10} vertical level, the bandpass filters allow a maximum of 500 Hz to enter, therefore, the sampling rate, according to the Nyquist theorem, needs to be at least 1000 sample/sec (500Hz×2). For this reason, this paper uses a sample rate of 1024 samples/sec to prevent noise and provide accurate data on muscle activity. The proposed system as seen in Fig. 4 is composed of electrodes, an amplifier, a band-pass filter, an Arduino Mega 2560 microcontroller and a computer running MATLAB software for data analysis.

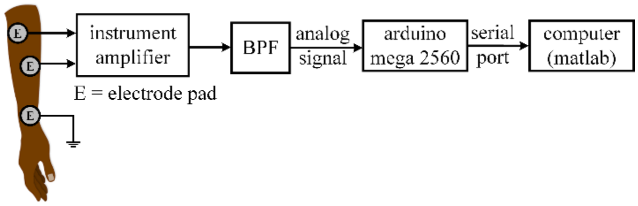


Fig. 4. Is a block diagram which displays the proposed method of collecting EMG data from the participants while they are performing the exercise.

E. *Hand-wrist joint movement [10]*

In this research, hand positions including flexion, extension, radial deviation, and ulnar deviation are important because they enable the precise detection and isolation of muscle activity in certain wrist muscles as shown in Fig. 5.

- Ulnar Deviation

Muscles that are activated include Flexor Carpi Ulnaris, and Extensor Carpi Ulnaris which allows an understanding of the activity and efficiency of these muscles during movements that involve wrist adduction as this position isolates the ulnar muscles. This is shown in Fig. 5 (a).

- Radial Deviation

Muscles that are activated include the Flexor Carpi Radialis, Extensor Carpi Radialis Longus, and Extensor Carpi Radialis Brevis. This position is useful for analyzing the function of these muscles in tasks that require wrist abduction and stabilization. This is displayed in Fig. 5 (b).

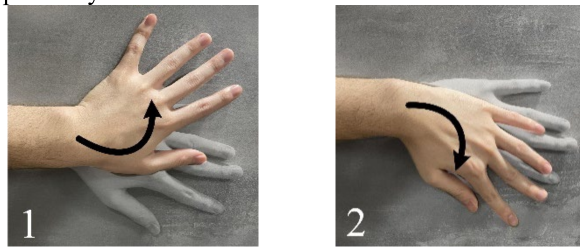
- Wrist Extension

Muscles that are activated include the extensor Carpi Radialis Longus, Extensor Carpi Radialis Brevis, and Extensor Carpi Ulnaris. This is useful for analyzing the activities that involve wrist stabilization and extension. This is portrayed in Fig. 5 (c).

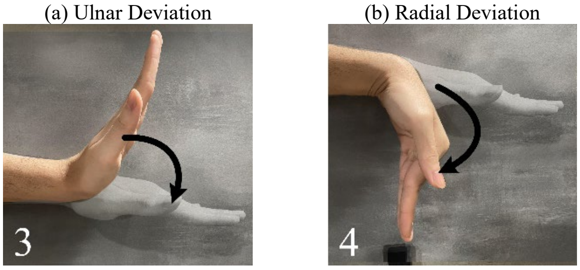
- Wrist Flexion

Muscles that are activated include Flexor Carpi Radialis and Flexor Carpi Ulnaris. This helps in understanding the activity and function of these muscles during wrist flexion movements. This is shown in Fig. 5 (d).

From now on, in this paper, the exercises in Fig. 5 (a) (b) (c) and (d) will be referred to as exercise 1, 2 , 3 and 4 respectively.



(a) Ulnar Deviation (b) Radial Deviation



(c) Wrist Extension (d) Wrist Flexion

Fig. 5. Hand-wrist joint movement.

F. Processing The EMG Signal in Time domain feature extraction

Time domain feature extraction is extracted to quantify the characteristics of the myoelectric signals.

1) Integrated EMG

Integrated EMG (IEMG) is a time-domain feature of EMG signals that provides a quantitative measure of the electrical activity produced by muscles. It is the sum of the absolute values of the EMG signal over a specified period. It is a cumulative measure that reflects the activity over a specified period. It provides a measure of the total muscular activity during that time frame [10].

$$IEMG = \sum_{i=1}^{N} x_i \tag{2}$$

where x_i is the individual EMG signal values and N is the number of samples.

2) Variance

Variance (VAR) is a statistical measure representing the spread or dispersion of data points. In the context of EMG signals, variance measures the variability of the muscle activation signal over a period of time. It provides a measure of the signal's amplitude and is calculated as:

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 \tag{3}$$

Where $\bar{x}$ is the mean of the EMG signal

3) Root Mean Square

Root Mean Square (RMS) is a normally applied measure of the differences between numbers which is predicted by a mode or an estimator. It is a statistical measure that provides the average magnitude of the EMG signal, representing the effective value of the fluctuating EMG signal. It is used to measure the amplitude of the EMG signal, often used to assess the muscle contraction force and is an accurate indicator of muscle activation levels [13] and calculated as:

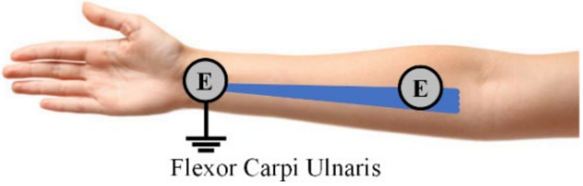
$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{4}$$

III. PROPOSAL

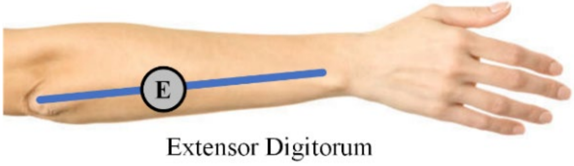
This paper proposes a method for objectively measuring the patient's real-time muscle strength through the use of surface electrodes on the patient-targeted muscle group connected to the physician's computer via the internet in an exercise during a remote physiotherapy session with a physician. The signal collection and conversion is shown in Fig. 4.

A. Method and procedure

This is done through data received from surface electrodes which were stuck on the Flexor Carpi Ulnaris muscle group and the Extensor Digitorum, both located in the forearm, shown in Fig. 6. Fig. 6 (a) displays the placement of the electrodes on the front of the forearm while Fig. 6 (b) shows the placement of electrodes on the back of the forearm. As the raw data is extremely small, it has to be processed through an instrumentation amplifier with a gain of approximately 100. The instrumentation amplifier also filters out unwanted noise. This signal is then sent through an Arduino Mega 2560 to convert the analogue signal into a digital signal via a sample and hold technique which allows for the computer software to detect and process the data.



(a) front of forearms



(b) back of forearms

Fig. 6. forearm electrode placements.

B. *Classification*

The participants were then asked to perform the first action, radial deviation, repeatedly following the beat of a metronome set at 15 beats per minute, switching between contraction and rest every other beat. This was repeated for the other 3 exercises in the order Radial deviation, Wrist extension and Wrist Flexion. This was recorded for 30 seconds. The data received from the participant is plotted on the time domain and for each exercise the participants performed. From this, the IEMG was found using (2). Then the Variance was found using (3) to be used in determining the spread of data. Finally, (4) was used to find the RMS of the data from the participants. This was used to analyze the data to create time domain graphs and box plot diagrams as seen in IV.

IV. EXPERIMENTAL RESULTS

Experiments were carried out to ensure the two proposed experimental methods are viable. In this section, there will be a discussion about how the EMG signal was processed using the proposed methods and an analysis of the results. Twenty participants, 10 men and 10 women, ages 16 to 60 years were used as the sample of this experiment. The EMG signals were recorded using 3 electrodes, shown in Fig. 6. Electrodes were placed on the forearm muscle group and the participants carried out exercise Fig. 5 (a) following the experimental procedure. This was repeated for the 3 other exercises.

A. *Instrumentation Amplifier*

In this experiment, the use of an instrument amplifier was necessary as recommended in the Principles section of this paper. Using an instrumentation amplifier has many advantages such as having a higher degree of accuracy and stability than other types of amplifiers. A schematic of the circuit can be seen in Fig. 2. As seen in the schematic, the circuit contains 7 resistors. Resistors R_1, R_2 and R_3 all have a resistance of 10 kΩ with only 1% error. This resistance was inputted into (1) for a gain of 101 and the resistance of resistor R_g was found to be 200Ω.

To ensure that the amplitude of the EMG data passed through the instrumentation amplifier is not affected, the frequency response of the instrumentation amplifier was determined. This was done by giving the amplifier an input of sinusoidal waves that had an amplitude of 50 mV with frequencies ranging from 0.1 to 1000 Hz. The results of the frequency response of the instrumentation amplifier for this experiment was then plotted in a graph as seen in Fig. 7. From this graph, the instrumentation amplifier used has a constant gain for frequencies under 10kHz. Therefore, this instrumentation amplifier is suitable for use in this research as the frequency of the waves from the EMG will be no more than 500 Hz due to the bandpass filter.

B. *EMG Results*

The data was then plotted in the time domain and the IEMG was extracted to be used in the classification.

The first method normalized all the data from each participant for each of the exercises. This data was then plotted onto a time domain graph as seen in Fig. 8. The RMS was then calculated for each exercise for each participant and was plotted as a line on the participant's time domain graph. From this, we can conclude that any EMG value above the RMS could be considered a peak of strength during the time period of the exercise which would display when exactly the exercise was performed.

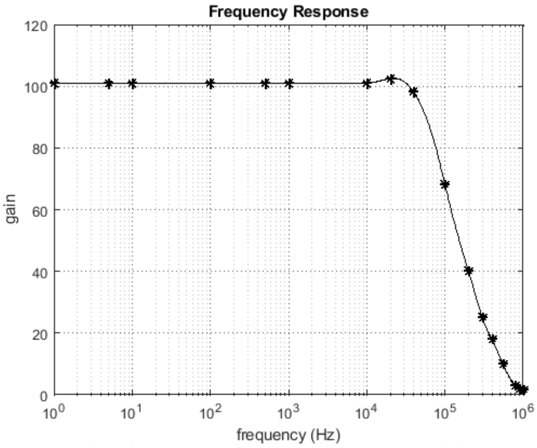


Fig. 7. A graph to demonstrate the frequency response of the instrumentation amplifier.

C. *IEMG Results*

The second method used the EMG data to find the IEMG, VAR and RMS via (2), (3) and (4) respectively as seen in TABLE I. For each exercise, the quartiles were calculated. The first quartile was 6635.59, 4974.57, 2016.64 and 3431.25 for exercises 1,2,3 and 4 respectively. The second quartile was 7454.54, 5555.53, 2266.32 and 3809.64 for exercises 1,2,3 and 4 respectively. The third quartile was 7832.90, 5923.88, 2695.69 and 4110.62. After finding the quartiles, box plots were created for each exercise. The box plots were then combined into one graph for comparison as seen in Fig. 9. Any outliers were also plotted in this graph.

The interquartile range (IQR) of each exercise was calculated to be 1197.31, 949.31, 679.05 and 1339.37 for exercises 1, 2, 3, and 4 respectively. As seen in Fig. 9, although the scaled data range of each box plot does overlap, the IQR of each box plot does not. This allows for the exercises to be differentiated as each exercise has its own IEMG magnitude. Therefore, the IEMG can be used to classify each exercise on its own.

V. CONCLUSION

In this research, the participants carried out four exercises which were then plotted in the time domain for analysis to see if the aims of this research are viable. The EMG signal was then plotted in the time domain. Three features of the time domain of the EMG were then extracted to be used for the analysis: IEMG, VAR and RMS. From the time domain graph, the strength used during an exercise could be concluded and the exercises were found to be classifiable from the box plot diagrams. The aim of this research was to find a method of improving telerehabilitation by giving physicians more objective data to work with during their appointments with patients in telerehabilitation programs. The findings from this paper could be implemented into a real-life telerehabilitation consultations by having the patient attach on the electrodes onto their targeted muscle group and having them perform the exercise as usual. Additionally, a programme could be created to automatically detect and classify the exercise that the patient is performing. This would require further research into the classification of a larger range of exercises. Machine learning could be implemented using our experimental conditions to create this programme.

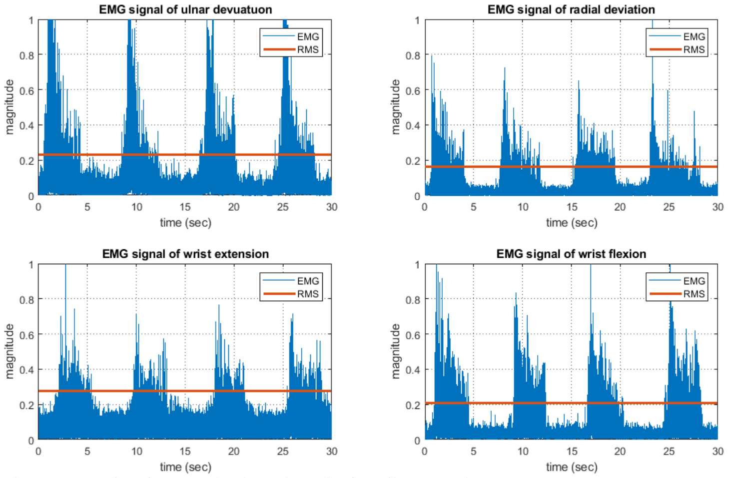


Fig. 8 example of IEMG in time domain for all 4 exercises.

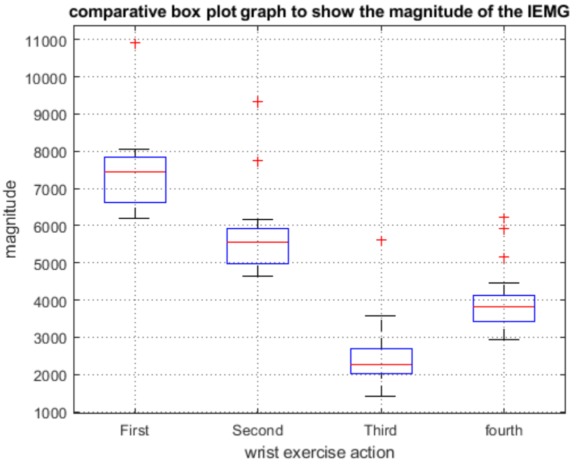


Fig. 9. a boxplot of the IEMG data from the sample.

TABLE I. THE IEMG, VAR AND RMS OF ALL THE DATA

No.	**Integrated EMG (IEMG)**				**Variance (VAR)**				**Root mean square (RMS)**			
	1	***2***	***3***	***4***	***1***	***2***	***3***	***4***	***1***	***2***	***3***	***4***
1	7516.4	5299.8	3092.3	5914.6	4.75E-07	2.99E-07	6.33E-07	1.06E-06	1.21E-01	9.59E-02	1.39E-01	1.81E-01
2	7846.6	5943.5	2822.9	4011.5	7.34E-07	4.31E-07	4.76E-07	4.45E-07	2.30E-01	1.60E-01	2.75E-01	2.07E-01
3	10911	9335.5	2822.9	3139.8	2.65E-06	1.94E-06	4.76E-07	1.75E-07	2.85E-01	2.44E-01	1.21E-01	7.33E-02
4	6539.6	4644.0	2256.8	3413.9	1.75E-07	1.76E-07	3.92E-07	2.77E-07	7.33E-02	7.35E-02	1.10E-01	9.23E-02
5	6192.0	6170.4	2390.4	3428.0	1.81E-07	5.61E-07	4.47E-07	2.35E-07	7.47E-02	1.31E-01	1.17E-01	8.50E-02
6	7452.8	4870.9	1416.7	3434.5	7.07E-07	1.88E-07	1.69E-07	2.52E-07	1.47E-01	7.61E-02	7.21E-02	8.80E-02
7	6339.7	4926.7	1977.5	3725.9	1.41E-07	1.94E-07	3.42E-07	2.56E-07	6.59E-02	7.71E-02	1.02E-01	8.87E-02
8	8064.3	4684.4	2067.2	2929.1	8.89E-07	1.80E-07	4.66E-07	1.34E-07	1.65E-01	7.43E-02	1.20E-01	6.43E-02
9	6730.5	5861.7	2410.6	3536.0	2.41E-07	4.61E-07	5.00E-07	2.44E-07	8.61E-02	1.19E-01	1.24E-01	8.65E-02
10	6616.8	4891.8	1659.0	3959.3	2.01E-07	2.20E-07	2.80E-07	3.60E-07	7.86E-02	8.23E-02	9.28E-02	1.05E-01
11	7456.3	5666.6	2055.8	4034.9	4.16E-07	4.43E-07	3.62E-07	3.57E-07	1.13E-01	1.17E-01	1.06E-01	1.05E-01
12	6978.6	5432.9	-	3687.8	3.01E-07	3.52E-07	-	3.36E-07	9.61E-02	1.04E-01	-	1.02E-01
13	7810.4	5022.5	2184.5	3687.6	9.21E-07	2.19E-07	5.13E-07	3.25E-07	1.68E-01	8.21E-02	1.26E-01	9.99E-02
14	7153.5	5904.3	2568.5	4457.8	3.86E-07	5.59E-07	6.10E-07	5.80E-07	1.09E-01	1.31E-01	1.37E-01	1.33E-01
15	6654.4	5722.0	1871.0	3131.7	1.58E-07	4.51E-07	3.70E-07	2.48E-07	6.96E-02	1.18E-01	1.07E-01	8.72E-02
16	7463.9	5587.1	2258.6	4186.4	4.14E-07	4.13E-07	4.52E-07	4.37E-07	1.13E-01	1.13E-01	1.18E-01	1.16E-01
17	6309.9	5523.9	2274.1	3893.4	1.32E-07	3.49E-07	4.14E-07	2.91E-07	6.36E-02	1.04E-01	1.13E-01	9.46E-02
18	8023.9	6165.1	2331.1	5148.9	5.47E-07	5.47E-07	4.10E-07	7.02E-07	1.30E-01	1.30E-01	1.12E-01	1.47E-01
19	7819.2	7744.2	5605.2	6229.5	3.57E-07	9.17E-07	2.01E-06	1.11E-06	1.05E-01	1.68E-01	2.49E-01	1.85E-01
20	7857.4	5483.4	3576.2	4031.2	4.95E-07	3.83E-07	8.47E-07	4.14E-07	1.23E-01	1.09E-01	1.61E-01	1.13E-01

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