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A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control

Levi Hargrove *, Kevin Englehart, Bernard Hudgins

Institute of Biomedical Engineering, Department of Electrical and Computer Engineering, University of New Brunswick, P.O. Box 4400, Fredericton, NB, Canada E3B 5A3

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Abstract

Pattern recognition based myoelectric control systems rely on detecting repeatable patterns at given electrode locations. This work describes an experiment to determine the effect of electrode displacements on pattern classification accuracy, and a classifier training strategy to accommodate this degradation. The results show that electrode displacements adversely affect classification accuracy, but training the system to recognize plausible displacement locations mitigates the effect. Furthermore, a combination of time-domain and autoregressive features appears to yield the best classification accuracy and is least affected by electrode displacements.

Keywords: EMG; Myoelectric control; Pattern recognition; Powered prostheses; MES

1. Introduction

Information extracted from multi-channel surface myoelectric signal (MES) recording sites can be used as inputs to control systems for powered prostheses. Myoelectric control systems can be loosely grouped into two categories; (1) conventional myoelectric control, and (2) pattern recognition based myoelectric control strategies. Conventional myoelectric control strategies have found widespread clinical use and have evolved to be used in conjunction with body powered harnesses, mechanical switches, and force sensitive resistors as part of an overall conventional prosthesis control strategy.

When fitting conventional prostheses it is common to embed electrode pairs in the prosthesis socket such that a bipolar channel is located over a muscle remaining on the residual limb. For transradial amputees, a common electrode placement would be one bipolar channel over the wrist flexors muscle group and one bipolar channel of the wrist extensor muscle group. A clinician would then instruct an amputee to produce muscular contractions to determine an appropriate MES amplitude threshold to activate the device. This type of conventional control strategy has proven to be relatively impervious to slight electrode displacements associated with socket/residual limb misalignments, as relatively coarse amplitude information is used.

Pattern recognition based myoelectric control systems operate on the assumption that at a given set of electrode locations, the set of features describing the myoelectric signals will be repeatable for a given state of muscle activation and will be different from one state of activation to another [1]. This form of myoelectric control has been implemented successfully by a number of groups in a controlled research setting; however, it has seldom been implemented clinically. Consequently, long term robustness issues, including sensitivity to electrode displacements, have rarely been considered.

Generally, pattern recognition based myoelectric control can be considered a supervised classification problem; training data are collected during a controlled experiment and a set of class labels are appropriately assigned to train the system. It is important that a wide variety of exemplars are presented to the classifier during the training phase so that it will generalize to new patterns presented during normal operation. This can be challenging for myoelectric control problems because the measured myoelectric signal changes for a variety of reasons. In a clinical setting it is important to complete the training data collection in a reasonable amount of time for the comfort of

* Corresponding author. Tel.: +1 506 458 7032.
E-mail address: levi.hargrove@unb.ca (L. Hargrove).

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both clinician and patient. Normally, training data are collected only from the nominal electrode placements (the location where the electrodes rest when the socket is in perfect alignment), and no effort is made to incorporate displacement locations which may be present due to socket/residual limb misalignment.

Intuitively, one would expect that electrode displacement would cause changes in the response of the control system; however, Hudgins et al. [2] found that shifts of up to 2 cm had relatively little effect on classification accuracy of a 5-class myoelectric control problem (elbow flexion, elbow extension, hand open and hand close). To obtain these results, a single bipolar channel of MES data were collected where one electrode was placed on the biceps and one electrode was placed on the triceps. Hudgins suggested that the electrode shifts were small in comparison to large the interelectrode distance and in both cases the electrodes were recording the global activity of the biceps and triceps.

Hargrove et al. [3] found that shifts of 1 cm from a nominal training position reduced classification accuracy from approximately 90 to 60% for a 10-class myoelectric control problem. When a classifier was trained to recognize plausible displacement locations, this classification accuracy dropped to only 85%. To obtain this result, four closely spaced bipolar (interelectrode spacing of 2 cm) channels were collected.

The results of these two studies imply that the classification accuracy changes due to electrode displacements are affected by interelectrode spacing, the number of electrodes used in making classifications, and the number of motions classified. It should be noted in both previously mentioned cases time-domain (TD) features were chosen to represent the MES waveforms. Furthermore, in each of those experiments, the electrodes were re-applied at displacement locations prior to collecting test data. Consequently, it was impossible to separate the classification error solely due to the electrode displacements from inevitable variability in the MES due to 'operator error' (slight differences in contraction patterns, and the inherent variability of the MES). This experiment is meant to investigate the effect of electrode displacements on classification accuracy for selected wrist and hand motions. Nominal and displacement data will be collected simultaneously using a high-density electromyography system to remove the effect of the operator error.

2. Experiment

2.1. Methods

When assessing classification accuracy of pattern recognition based myoelectric control, bipolar electrode pairs are typically placed in nominal locations over areas of interest. However, to accomplish the goal of assessing the effect of electrode displacement, five constellations consisting of ten monopolar electrodes (Fig. 1a) were applied to the upper forearm (Fig. 1b). The interelectrode spacing in the constructed bipolar pairs was 3 cm, and displacement electrodes were located 1 cm from the center electrodes at 45°. The nominal electrode position would be constructed by taking difference between electrode C and H. This electrode location corresponds to the center of the constellation and would be the expected location of the recording electrode during the day-to-day operation of the prosthesis. Shift locations correspond to the differences between AF, BG, DI and EJ, assuming a rigid bipolar electrode pair. These locations represent plausible worst case possible displacement locations if there was socket/electrode misalignment. Thus, by recording the monopolar channels from the constellation, four displacement locations could be investigated without having the subject repeat the motions separately for each displacement situation. This removes 'operator error' from the analysis.

A high density EMG system (TMS International REFA 128) which is capable of collecting up to 128 monopolar MES channels was used to collect MES data from four normally limbed subjects to with electrodes placed to model long transradial amputees. The experimental protocol was approved by the University of New Brunswick's Research Ethics Board.

For consistent electrode placement, each subject was instructed to place their right arm in a fully supinated position on a table. Next, constellation 1 was placed on the top of the forearm (12 o'clock position), approximately 1/3 the distance from the

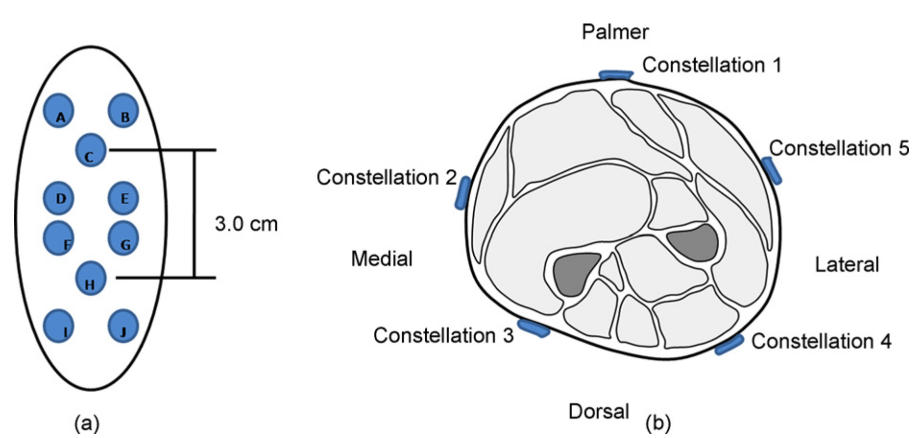

Fig. 1. (a) An example of the monopolar electrode constellation used to investigate electrode displacements. Bipolar spatial filters were created offline using C–H, A–F, B–G, D–I, G–J. (b) Each constellation was placed 1/3 the distance between the elbow and wrist at the locations shown above.

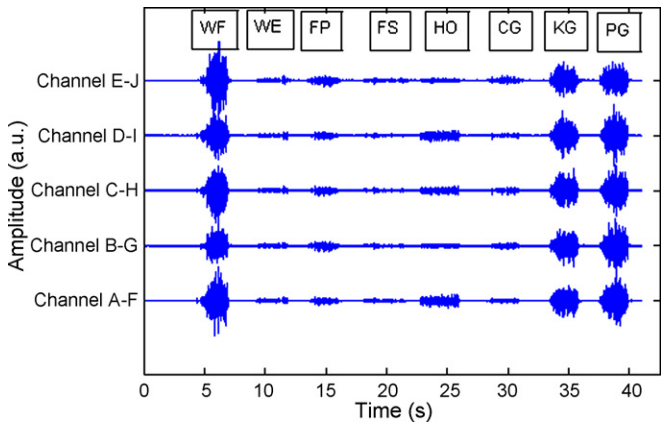

Fig. 2. An example recording taken from one constellation (position 2 in Fig. 1(b) for eight motion classes. The bipolar channels correspond to the constellation locations shown in Fig. 1a.

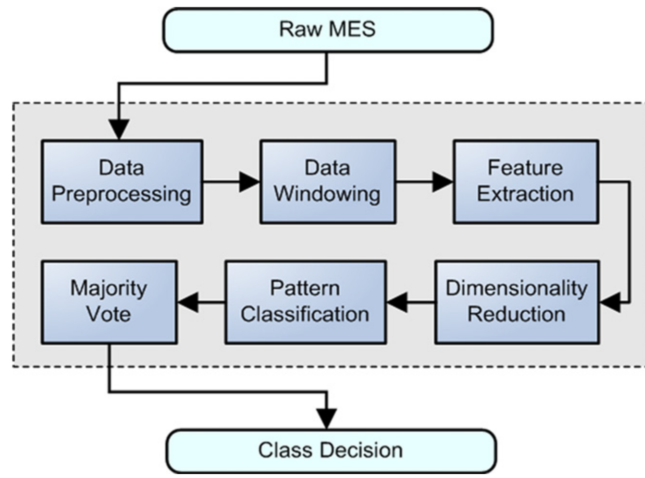

Fig. 4. A block diagram showing the state-of-the-art in pattern recognition based myoelectric control.

elbow to wrist. The remaining four constellations were placed equidistantly around the circumference of the forearm, and a reference electrode was placed on the wrist. The five electrode constellations corresponded to 50 monopolar electrodes in all.

After electrode placement, data were collected during 11 motion classes corresponding to forearm pronation (FP), forearm supination (FS), wrist flexion (WF), wrist extension (WE), hand open (HO), chuck grip (CG), key grip (KG), power grip (PG), fine pinch (FP) grip, tool grip (TG), and no motion (NM). The subjects were instructed to start from rest, elicit a moderate constant force isometric contraction for 5 s and then return to rest. Five repetitions were collected for each motion, corresponding to 25 s of active data for each motion class. All data were then manually segmented as described in Zhou et al. [4].

2.2. Signal processing

All raw data were sampled at 2000 Hz and highpass filtered with a 3 dB cutoff frequency at 20 Hz to reduce motion artifact. An additional 6th order notch filter (fc 55–65 Hz) was used to remove powerline frequencies. After filtering, appropriate bipolar channels were created and inspected visually to ensure that the recordings were of high quality and each channel had similar noise floors. Fig. 2 displays an example recording from the five created bipolar channels associated with an electrode constellation from a representative subject while Fig. 3 displays an example of the myoelectric patterns for eight motion classes acquired from the central biopolar electrode of each constellation.

It is apparent from Fig. 2 that the detected MES at all displacement locations located in the same constellation are similar; however, there are some slight differences in the waveforms. For example, the E–J channel has a slightly larger amplitude than the channel C–H while channel B–G has a slightly lower amplitude. In Fig. 3, it is apparent that the patterns are generally different across motions; however, in some cases, such as KG and PG motions, the patterns are very similar. It seems likely, therefore, that similar patterns may be

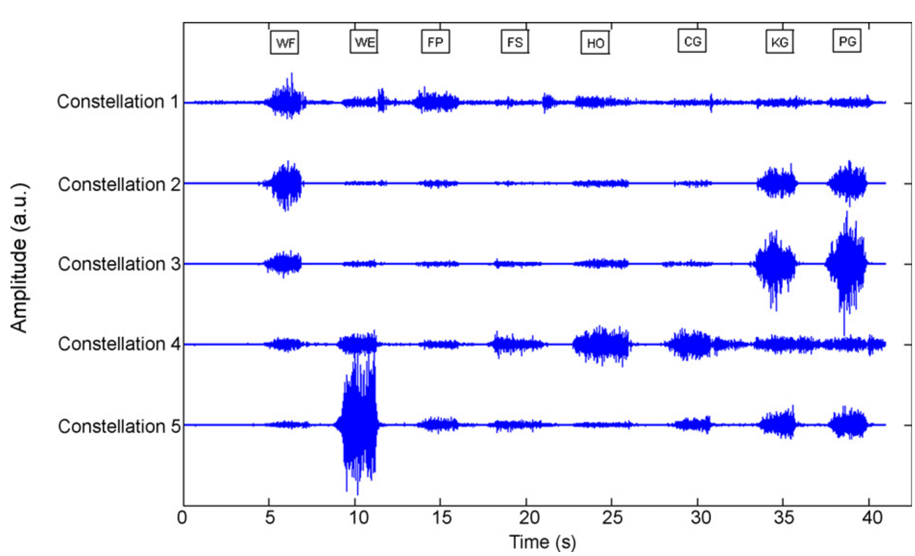

Fig. 3. An example recording taken from the center bipolar electrode (C–H) in each constellation for eight motion classes. It can be seen that the patterns for classes KG and PG are very similar.

erroneously classified if subjected to the effects of displacement, and thereby affecting the overall classification accuracy.

The block diagram shown in Fig. 4 illustrates the key components in a pattern recognition based myoelectric control scheme.

Wide variety of feature sets, dimensionality reduction, and classifiers have been investigated in the literature [5–14]. A convenient and functional configuration consists of a series of TD or autoregressive (AR) features as inputs to a linear discriminant analysis (LDA) classifier. This configuration has been shown to yield good classification accuracies [4,15] and is computationally efficient, facilitating embedded systems implementations. The TD feature set has been described in detail in previous work, and detailed descriptions of the features are available in [2]. In the subsequent analysis, the control scheme comprises TD and/or AR features extracted from 150 ms analysis windows with an uncorrelated linear discriminant analysis (ULDA) dimensionality reduction [16] classified by a Bayesian LDA classifier.

As previously indicated, 25 s of active data were recorded from each motion class. Two different training strategies were employed to train the pattern recognition system; (1) center training, and (2) grouped training. In the *center training* method, only the first 12.5 s of data collected from the center of each constellation (constructed from electrodes C and H) were used to train the system. If one were expecting a perfect socket fit with no displacements this would be an appropriate training strategy; however, tin the presence of displacements this is not a rich training set and is not an ideal training strategy. The remaining 12.5 s from the displacement locations were used to test the system. In this training strategy no exemplars from possible displacement locations are presented to the classifier.

In the *grouped training* method, the first 12.5 s of data collected from each of the bipolar channels constructed in each constellation were used to train the system. The remaining 12.5 s collected from the displacement locations were used to test the system. This situation represents the clinical training process of a pattern recognition based myoelectric control system. In this training strategy, exemplars from possible displacement locations are presented to the classifier in hopes that a classifier trained using the rich training set will be better able to recognize motions should a shift occur. If one is expecting any socket misalignment the 'grouped training' method is a more appropriate, yet less convenient training strategy.

In addition to center training, and grouped training, a separate pattern recognition system was trained and tested separately for each possible displacement location. Once again the first 12.5 s of data were used to train the system and the second 12.5 s were used to test the system. This was done to provide an estimate of the maximum possible classification accuracy that a subject was able to attain without electrode shifts for the motions under investigation using only five input channels; one from each constellation. This provides an indication of the importance of electrode site selection, under conditions of no shift after training. In the plots shown in Figs. 5 and 6 the maximum possible classification accuracy attained is annotated as 'local training'.

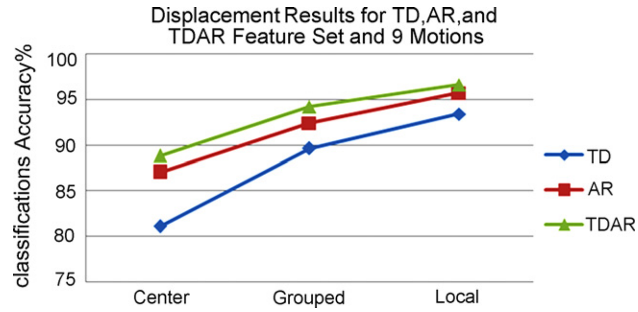

Fig. 5. Classification accuracy resulting from using TD, AR, and TDAR feature sets to classify nine motion classes. Results are averaged over all subjects and displacement locations.

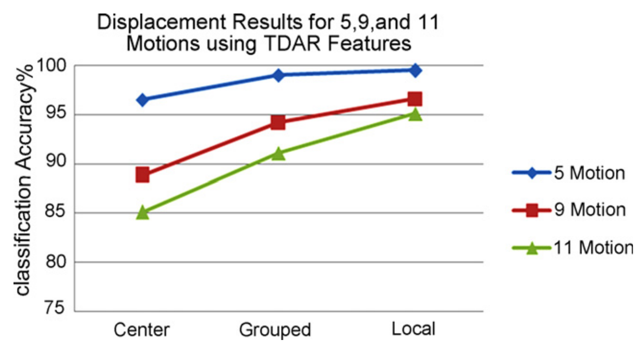

Fig. 6. Classification accuracy resulting from using TDAR feature sets to classify 5, 9 and 11 motion classes. Results are averaged over all subjects and displacement locations.

Three different control schemes were trained using each of the previously described strategies; a 5-motion class case, a 9-motion class case, and an 11-motion class case.

3. Results

Fig. 5 displays the result of the two training methods to classify a subset of 9 of the collected motions. Classification results obtained using TD features, AR features, and a combination of TD and AR features (TDAR) are displayed on the plot. The 9-motion class subset corresponded to WF, WE, FP, FS, HO, CG, PG, KG, and NM. Although the results for the 5- and 11-motion class cases are not shown, they both display the same trend as the 9-motion class case.

A two-way ANOVA was performed and it was found that training strategy significantly affected classification accuracy ($p < 0.01$) and that TDAR features outperformed both TD and AR feature sets ($p < 0.05$). Interestingly, no significant subject effect was found, indicating that each subject's performance was very similar and may be attributed to the fact that all subjects were well-trained users and had participated in previous pattern recognition sessions.

Tables 1 and 2 display confusion matrices for the 9-motion class case classified the TDAR feature set.

Fig. 6 displays the result of investigating the three different motion class cases using the three different training strategies. The 5-motion class subset included the motions FP, FS, HO, PG, and NM. In making the comparison, TDAR features were

Table 1
Confusion matrix for the 9-motion class case classified using TDAR feature set with the center training strategy averaged across all subjects and displacement locations

Prompted motion	Predicted motion								
	WF	WE	FP	FS	HO	CG	KG	PG	HO
WF	89.2		0.9	1.3	1.1	0.1	1.5	5.8	
WE		97.5		0.1	0.6	1.3	0.5		
FP		1.0	82 8	0.2	1.0	10.6	4.2		
FS		0.4		94.3	0.4	1.1	3.9		
HO		0.2		2.4	93.8	0.3	3.2		
CG			0.6	3.3	2.7	92.2	1.1		
KG		0.1		0.5	0.3	4.8	90.9	3.4	
PG				0.8	1.6	1.1	32.1	64.4	
HO	0.0	0.7	1.9			0.5	0.1	0.3	96.5

The desired motion is displayed in the row, and the percentage of time each motion class was predicted is shown in the columns.

Table 2
Confusion matrix for the 9-motion class case classified using TDAR feature set with grouped training strategy averaged over all subjects and displacement locations

Prompted motion	Predicted motion								
	WF	WE	FP	FS	HO	CG	KG	PG	HO
WF	94.6		1.0	0.4	0.5	0.2	0.7	2.7	
WE		98.5		0.1	0.6	0.8			
FP		0.3	94.2	0.5	0.5	3.5	1.0		
FS		0.1		96.4	1.3	0.8	1.4		
HO			0.1	1.1	97.3	0.2	1.2		
CG			0.7	1.6	0.2	97.2	0.4		
KG				0.5	0.1	3.8	90.6	5.1	
PG				0.4		0.3	18.7	80.5	
HO						0.3			99.7

The desired motion is displayed in the row and the percentage of time each motion class was predicted is shown in the columns.

used; however, the same trend in the results was seen for the TD, and AR feature sets.

A two-way ANOVA showed that classification accuracy is significantly affected by training strategy ($p < 0.01$) and the number of motions classified ($p < 0.01$). No significant subject affects were found.

4. Discussion

Figs. 5 and 6 support the hypothesis that electrode displacements result in less accurate pattern recognition based myoelectric control systems. The effect of displaced electrodes can be mitigated by training the classifier to recognize plausible displacement locations; however, the grouped training strategy will not return the classification accuracy to the best case scenario of training the classifier at specific non-displaced locations. If center training is used the classification accuracy drops from approximately 93 to 87% for the TDAR feature set classifying nine motion classes. If using the TD feature set, the drop is from 90 to 81%. Although the relationship between classification accuracy and prosthesis usability has yet to be clearly defined [17], it is highly likely that accuracy drops of this magnitude will severely affect the usability of the device. The classification accuracies found using the local training strategy are comparable to classification accuracies found previously using similar experimental protocols [15]. Furthermore, it did not matter which bipolar pair was used in the constellation, the control system yielded similar classification accuracies. This highlights the insensitivity of pattern recognition based myoelectric control systems to nominal electrode placement locations so long as the system is trained and tested at the same location.

These results also clearly illustrate the necessity of presenting a wide variety of exemplars to a classifier in a supervised classification problem. The 'grouped training' method contains more exemplars and is the proper way to train the classifier; however, even though the 'center training' method is not ideal, it is used almost exclusively, for convenience. In practice, plausible displacement locations should be incorporated into the training data set. Plausible displacement locations will need to be determined by a clinician as the degree of socket/residual limb misalignment will be dependent on how secure a fit may be established. This, in turn, will be dependent upon the skill of the prosthetist, the nature of the amputation, and the magnitude of external loads imposed on the prosthesis.

There was no apparent relationship between displacement direction and classification accuracy. For some subjects displacement in upper left direction yielded very poor classification accuracy while for other subjects displacement in the upper left direction yielded very little change from the nominal classification accuracy at the center location. This is not a surprising result as the signals depend on the underlying muscles and there are undoubtedly anatomical differences between users.

Upon closer investigation of the confusion matrices displayed in Tables 1 and 2 it can be seen that grouped training improves classification accuracy across all classes in comparison to center training. The majority of classification errors when using grouped training are due to confusion between grip types. These motions use similar muscles and consequently it is more difficult for the pattern recognition system to discriminate between them. Group training also drastically improved the forearm pronation class. When looking at the patterns displayed in Fig. 3, it can be observed that the forearm pronation class is very similar to the chuck grip class.

The AR, and TDAR feature set performed significantly better than the TD feature set in this work. Furthermore, the degradation due to displacements was more pronounced for the TD feature set. This suggests that AR coefficients may be more robust to electrode displacements. When the grouped training strategy was used, all three feature sets displayed much less degradation, and the difference between TD and AR was not as pronounced.

The results of this experiment generally agree with those found previously; training at plausible displacement locations mitigates the effect of electrode displacements. It should be noted that the classification degradation due to displacements was less pronounced in this work. There are several possible reasons for this difference. One possible reason for this is that five MES channels were used in this work whereas only four channels were used in a previous experiment. A second possible reason is that this work considered slightly different motion classes than previously investigated; wrist abduction and adduction were not considered in this experiment whereas they were considered in previous work. A third possible reason is that a slightly wider interelectrode spacing was using in this experiment. Consequently, the relative electrode shift in comparison to interelectrode distance was smaller in this experiment.

This work highlights how changes in patterns detected at electrodes affects pattern recognition based myoelectric control. In this instance, changes in patterns were due to electrode shifts, but any other mechanism which create pattern changes at the electrodes, such as changes in electrode impedance, changes due to fatigue or changes in loading, may cause classification degradations. To compensate for these changes, the system must be trained very carefully such that the exemplars coinciding with each of these conditions are included in the training data.

5. Conclusion

This investigation clearly indicates that greater robustness to electrode shifts within the socket of an upper limb prosthesis may be obtained by including exemplars of those possible shifts. Current work is focused upon quantifying electrode shifts that occur *in situ* during normal use, including a variety limb positions and external loads. A practical means of delivering these benefits is under consideration, including a systematic displacement of the electrodes during training, and the idea of a ‘‘training electrode’’ which would provide all shifted locations as described in this work.

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