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EEG Dimension Reduction in Motor Imagery-based BCI Approach

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Abstract: Although a significant number of studies have been devoted to the investigation of the electrographic correlates and neurophysiological mechanisms of voluntary movement and motor imagery-related brain activity, there is a question on which EEG characteristics reflect its content. Considering that motor imagery is a complex cognitive process which requires coordinated activity of a number of cortical structures of the hemispheres, the EEG dimension reduction problems were studied. The values were recorded from 14 channels in eight subjects in the task of voluntary movement execution and motor imagery activity. The principal component analysis has shown that the orthogonal transformation of the EEG channels has formed of 3 components, sufficient to describe a multidimensional brain pattern. The description of invariant EEG patterns of voluntary movements and motor imagery can be performed on the basis of a compressed set of features of the covariance matrix. It has been shown that frontal and central areas as critical brain structures controlling behaviour predominantly participated in the performance of movement execution. Whereas under conditions of motor imagery-related brain activity, the loci remaining in the primary motor cortex were additionally formed in the parieto-occipital associative regions of the brain, with a partial dominance of the right hemisphere. The eigenvectors of target spatio-temporal EEG patterns associated with the movements execution and motor imagery can be used as markers for classification in the BCIs.

Keywords: EEG, Movement Execution, Motor Imagery, Dimension Reduction, Component, PCA, LDA

1. Introduction

The creation of systems known today as the Brain-computer interfaces (BCIs) is one of the most rapidly developing areas of research, providing the possibility of communication of completely paralyzed patients with the outside world [1, 2]. Moreover, a number of authors consider this technology as a fundamentally new language and a channel of human interaction with the external environment through brain signals [3, 4].

The key element in implementing BCIs technology is the efficiency of setting in the stimulus-independent neural interface circuit, including methods and algorithms for the detecting of invariant EEG patterns [5, 6]. Along with numerous electrographic phenomena, for these purposes, cortical potentials are currently used during the implementation by the person of voluntary movement or their imagined equivalents [7, 3]. At the same time, the EEG classifier and methods of predicting and extracting features ensure the functioning of the neural interface from the point of view of recognition of control commands [8, 9]. In addition, the extraction of distinguishable features of EEG through methods of processing of the brain signals should ensure dynamic adaptability to the characteristics of quasi-stationary signals [7].

On the other hand, it has been shown that the effectiveness of BCI systems based on the EEG depends on a number of factors, the most important of which are the individual characteristics of the user and his current functional state [10]. The detection of EEG patterns associated with voluntary motor execution or motor imagery activity is also complicated by the presence of various types of artefacts in the recordings [9]. These factors, therefore, induce the search for ways to reduce data redundancy, reduce the dimension of the signal without loss and distortion of useful information to create effective BCI systems that demonstrate high accuracy and speed of voluntary control. The development of new methods of analysis and interpretation of brain signals can directly affect the reliability of the functioning of such a non-verbal and non-muscular control channel, as well as the efficiency of the classification of patterns of bioelectrical brain activity, providing the overall stability of the system [11, 12]. These conditions, as before, are decisive for accelerating the spread of neural control technology not only for research purposes, but also in the mass consumer market for solving problems of monitoring the functional state of a person, as well as forming a new non-muscle channel for controlling of various devices [13-16].

The goal of this study was to reduce multidimensional EEG and minimize the description of the target EEG features associated with voluntary movement execution and motor imagery activity by a combination of the Principal Component Analysis (PCA) method for the subsequent classification of the eigenvectors of the covariance matrix using the Linear Discriminant Analysis (LDA) method.

2. Materials and Methods

2.1. Participants

The study involved 8 people (4 men and 4 women), whose average age was 26±2 years. All of them had no experience of psychophysiological examinations, they were right-handed and had no health abnormalities. The study was conducted in accordance with the requirements of the SFedU Bioethics Commission, developed on the basis of the Declaration of Helsinki. All of them confirmed in writing their voluntary participation consent and were adapted to the conditions of the study.

2.2. Experimental Procedure

During the experiments, the participants were in a comfortable position (in a chair), in a light and soundproof Faraday chamber. Each of them participated in a training procedure and two test examinations. During the trainings, the subjects were asked to voluntarily perform a movement execution (raising the forearm in a vertical plane with the elbow joint resting on the armrest of the chair) with the right or left hand with an interval of 6-10 sec in any sequence but with the condition that after the movement execution their mental (motor imagery) repetition will be performed. After completing this complex, the subject was to signal the end of work by pressing a button. In the process of training, there was an adaptation to the conditions of the examination, an individual rate of movement performance was formed. At the same time, the individual speed characteristics of the subjects were determined. The training was carried out without EEG registration.

During the test examinations with the EEG recording, all participants first performed at least 30 real movement executions of the left or right hand in any sequence and at a voluntary pace with an interval of 6 and no more than 10 seconds between successive movements (series M). Then the subjects were asked to follow each real movement a similar motor imagery equivalent for 2 seconds (series M + MI). The signal of the end of motor imagery repetition was not required. In total, over 70 cycles (M + MI) were performed with both the left and right hand.

2.3. EEG Recording

The source of data for the analysis was artifact-free EEG segments recorded from 14 standard channels according to the international system "10-20", namely: f7, f8, f3, f4, c3, c4, p3, p4, o1, o2, t3, t4, t5, t6. EEG recording was carried out monopolar with referents located on the earlobes. Additionally, an electromyogram (EMG) was recorded of the superficial muscles of both arms, flexing the forearm at the elbow joint (m. Brachioradialis), and an electrooculogram (horizontal and vertical, EOG) to remove artefacts associated with eye movement and blinking. The sampling rate of the signal for each of the recording channels was 250 Hz. EEG signals were preprocessed with a 1-70 Hz bandpass filter and a 50 Hz notch filter. All registrations were carried out using the Encephalan biopotential amplifier (Medikom-MTD, Russia). Statistical analysis was carried out using the Statistica 12 software package.

2.4. EEG Analysis

Principal component analysis (PCA) was used to orthogonal transformation of a set of observations of potentially correlated variables (EEG channels) into a set of values (covariance matrix) of linearly uncorrelated variables called principal components. The number of principal components is usually less than or equal to the number of the original variables, and the principal components are independent only if the dataset is normally distributed. The transformation is performed in such a way that the first principal component has the maximum possible deviation, i.e., considers as much of the variability in the data as possible. Each next component, in turn, has the highest variance and orthogonal (i.e., not correlated) with the preceding components.

The calculation of the covariance matrix was carried out according to:

$$C = E[B \times B] = E[B * B^*] = \frac{1}{N} \sum_{i,j} B * B^*$$

where:

C – covariance matrix.

E – expected values.

B – deviations from the mean in each row m of the data matrix.

× – output values.

*– conjugate transposition.

N – is the number of columns in the dataset.

Canonical discriminant analysis or Fisher's linear discriminant was used as a linear classifier to separate more than two classes (from 3 to 5) of rest and movement-relate brain potentials based on the analysis of the eigenvalues of the covariance matrix. In the case when there are more than two classes, the analysis in calculating the discriminant functions can be extended in order to find subspaces, i.e., to separate all available classes while maintaining the lowest possible variance within the subspaces. The classical method for finding the best data discrimination is to find a canonical discriminant function d that can maximize the ratio of between-group variation to within-group variation:

$$\lambda = B(d)/W(d),$$

where:

B - intergroup, W - intragroup scattering matrices of the observed variables from the mean.

To determine the time windows for analysis and classification, we used the procedure of superposition and inverse averaging of signals relative to the marks of initiation of actual movement execution. The marks were installed offline after filtering additional myographic (EMG) channels with a bandpass filter (0.1-4 Hz) with a conditional threshold of 10 μV, corresponding to the onset of actual movement. For the analysis, we selected EEG epochs associated with the performance of movement preparation (MP) and motor imagery (MI) in two time windows: -500 ÷ -150 ms before the execution of a actual movement and +2500 ÷ +4500 ms during its mental repetition.

Determining the time spent on performing a motor imagery within the framework of the training procedure was reduced to measuring the interval between actual movement execution and pressing a button corresponding to the end of the motor imagery task. This interval was averaged 2550 ms (St_Dv -119.254; +119.256). Taking into account the phenomenon of β-synchronization (post-movement beta rebound (PMBR)), the duration of which, according to a number of authors [17], is up to 500 ms, as well as the time for the formation of a motor response (no more than 300 ms), the time spent on performing a motor imagery task was about 1750 ms. (St_Dv -119; +119). Additionally, correlation coefficients (CC) were calculated between the EEG and EMG signals (for the right and left hand) to exclude the influence of muscle artefacts. The analysis showed that the CC value did not exceed±0.16.

3. Results and Discussion

The analysis of the EEG spectral characteristics of the subjects recorded at rest with eyes open and closed before and after work showed that there were no significant differences between them in the frequency range from 1 to 70 Hz. This fact indicates the absence of any significant changes in the functional state of the central nervous system of the subjects during the experiment.

The principal component analysis (PCA) has shown that the orthogonal transformation of the original dataset leads to the formation of a limited number of components sufficient to describe a multidimensional EEG. PCA results are usually discussed in terms of the significance and sensitivity of the components (sometimes called factors) and the load (the weight of each standardized input variable to obtain a component score). As a result of the analysis, 4 main components were identified, 2 of which accounted for more than half of the load (up to 60%) of significant eigenvectors (Figure 1).

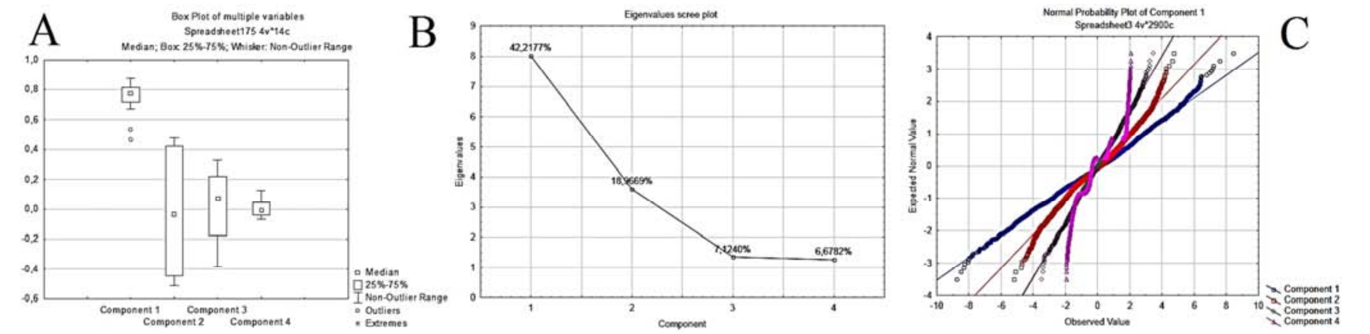

Figure 1. Graphical representation of the results of the PCA of the main components: A - mean and standard deviation of each component; B - component weights; C is the distribution of eigenvectors.

The first main component accumulated most of the RX variability in the data (i.e., all the maximum deviations in the values of the initial variables – EEG channels), which, apparently, is associated with fluctuations of brain states that are non-specific in relation to the actual movement execution or motor imagery activity being realized. Each next component had the maximum variance that orthogonal to the previous component. At the same time, of the 4 identified components, only the first three were significant (Table 1, Figure 2).

The second component (factor) turned out to be the most sensitive to intrahemispheric differences in the implementation of both movement execution and motor imagery. It reflected the presence of a connection between the working hand and the corresponding contralateral hemisphere of the brain (Figure 2.A, 2.B). The third component, with the lowest load among the significant factors (around 7%), was more sensitive to interhemispheric interactions in symmetrical brain regions and had no significant connections with the movement activity performed (Figure 2.A).

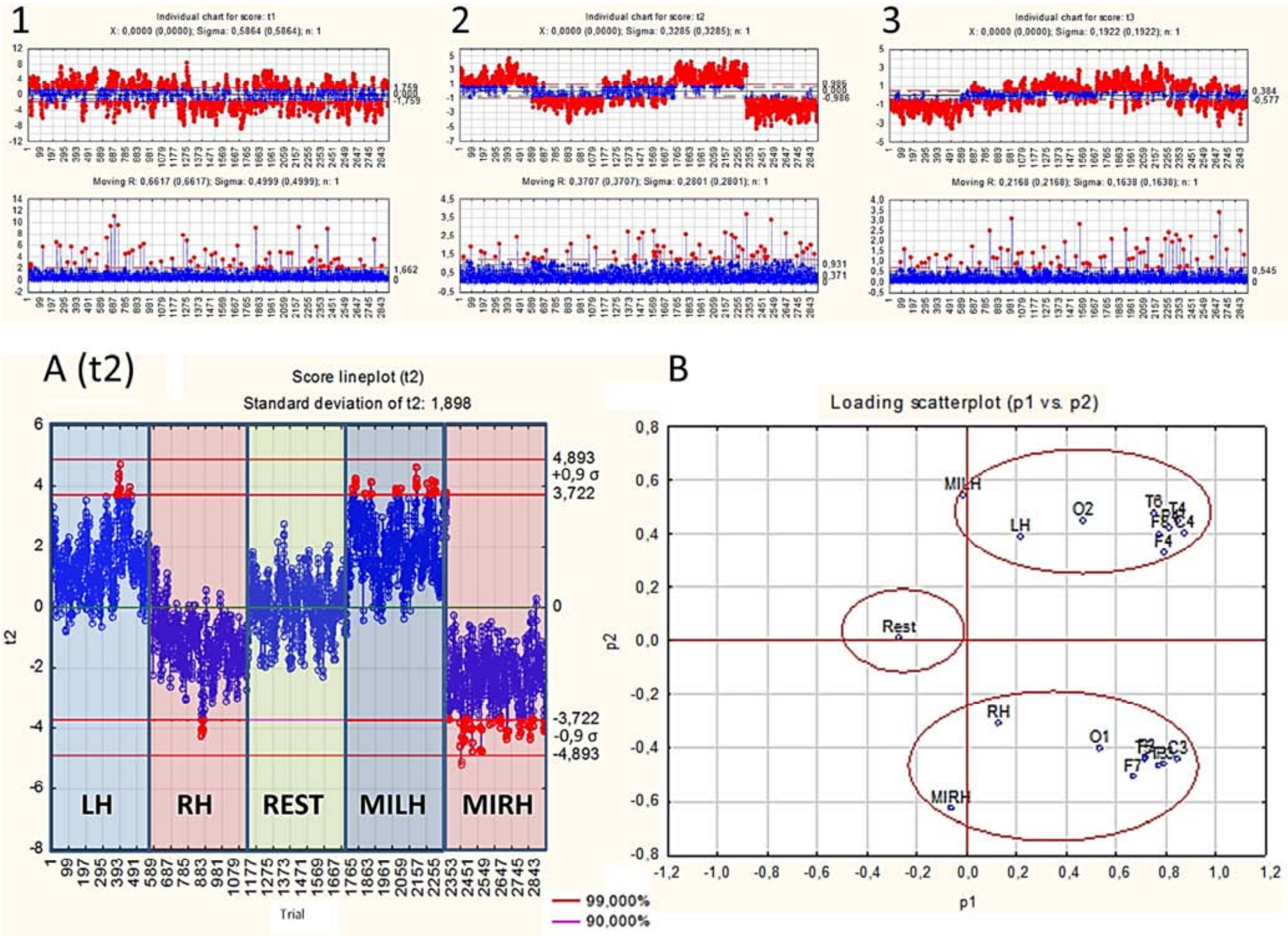

Figure 2. *Graphical representation of the results of PCA decomposition of the original EEG signal into components 1, 2 and 3.*

Legend: A - component / factor # 2; B - component composition / sensitivity of factors 1 and 2. LH - left hand, RH - right hand, Rest (R) – rest with eye open, MILH – motor imagery left hand, MIRH - motor imagery right hand.

Table 1. *The result of the analysis of the main components for 5 classes of events (actual movement, motor imagery and rest).*

Principal Components Analysis Summary. Number of components is 4. 74,9868% of Sum of squares has been explained by all the extracted components.							
Com.	**RX**	**Eigenval**	**Q**	**Limit**	**Q_Cum**	**Sign.**	**Iterations**
1	0,422177	8,021364	0,361650	0,052958	0,361650	S	8
2	0,189669	3,603710	0,250090	0,055881	0,521294	S	7
3	0,071240	1,353564	0,014406	0,059148	0,528191	S	50
4	0,066782	1,268854	-0,08814	0,062824	0,486602	NS	50

The structure of the first component largely met the requirements for stochastic (random) processes. It had a certain optimal amplitude, at which it manifested itself most strongly in comparison with the others principal components, and the signal also remained constant during the entire observation interval. The magnitude of the load of the first component significantly exceeded that of the second (on average, 2.22 times). Therefore, in the initial dataset, the changes in the EEG, which were non-specific in relation to the controlled activity, were as many times greater than the informative signal.

The discriminant analysis of the eigenvectors showed a significant increase in the accuracy of the classification of observations under conditions of decreasing data redundancy for the 3rd and 5th classes of classes. So, the application of the Fisher discriminant after the discovery of unique eigenvectors of movement execution and motor imagery made it possible with a high probability, approaching 92.8% (in some cases with an Error of 0.01), to find a subspace (0 is the root of the discriminant function) related to the idling state of the brain - rest (Table 2., Figure 3.C). In addition, roots (1 and 2) of discriminant functions (Table 2) were found, separating events associated with movement and motor imagery, as well as the left and right hands with a probability of up to 96% (Figure 3.B, C) that was not at all obvious in terms of determining the discriminant functions of the original data (Figure 3.A).

The greatest contribution to the classification of 5 classes, including the rest, movement execution and motor imagery was made by channels f3, f4, c3, c4, p4, with an R.Sqr coefficient of at least 0.95, as well as channels p3, t3, t4, t5, t6, o1, o2, at 0.8<R.Sqr<0.95. Significant channels for linear discrimination of 3 classes (motor imagery and rest) were c3, c4, p4, t5, t6, o2, t4 with R.Sqr>0.95, and f3, f4, p3, o1 with 0.8<R.Sqr<0.95.

Table 2. *The roots of discrminant functions applied to the covariance matrix of eigenvectors.*

№	Eigenvalue	Canon-R	Wilks'Lam	C_Sqr.	Df	p
0	24,265	0,980	0,016	11947	56	0,000
1	0,868	0,681	0,404	2616	39	0,000
2	0,318	0,491	0,755	810	24	0,000
3	0,004	0,065	0,995	12	11	0,339

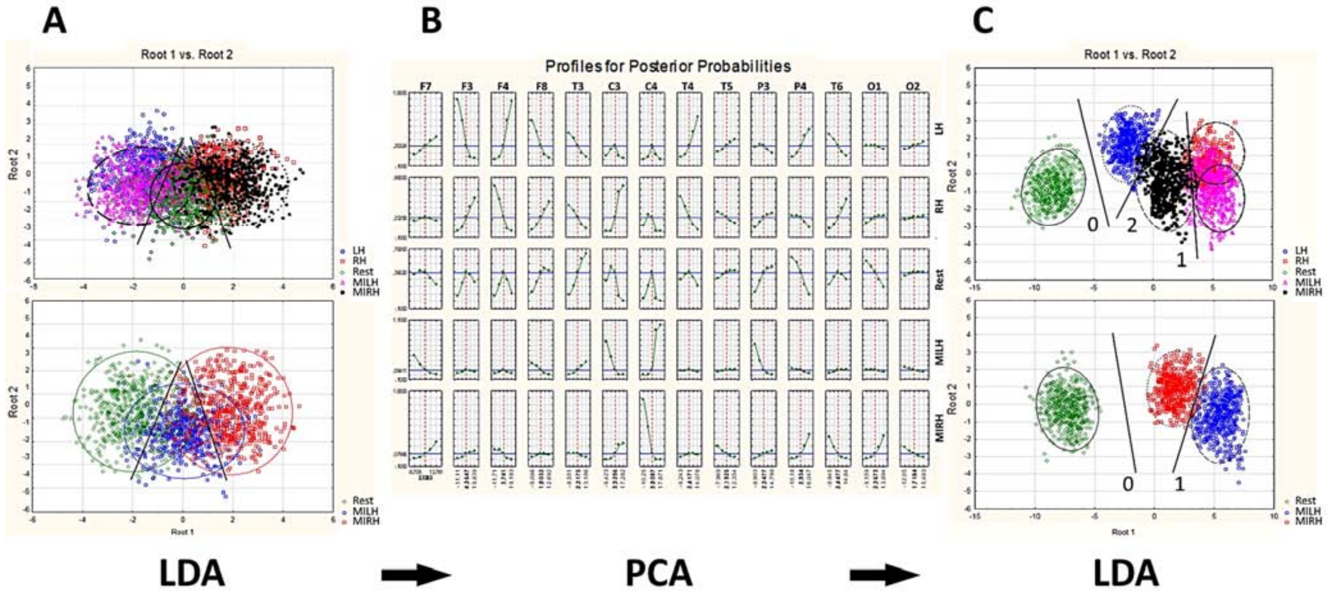

Figure 3. *The result of discrimination of the 5th and 3rd classes and the determination of the posterior probabilities of the covariance matrix for a group of 8 subjects.*

A - the result of discriminant analysis of the raw EEG; B - posterior probabilities of the classifying function; C - is the result of applying Fisher's discriminant to the covariance matrix after Principal component analysis (PCA). Classes: LH, RH, Rest, MILH, MIRH (see Figure 2).

It has been experimentally demonstrated that the spatial pattern distribution in the subjects in some cases was different in the process of movement and motor imagery-related brain activity [18, 19]. The frontal and central areas as critical brain structures for controlling voluntary behaviour predominantly participated in the movement execution, while under conditions of motor imagery brain activity, the target loci remaining in the primary motor cortex (M1) were additionally formed in the posterior parietal (associative) brain regions in a dominant left hemisphere [20]. On the one hand, Kai J. Miller and his colleagues experimentally demonstrated that the spatial distribution of the motor imagery-related neuronal population activity mimics the spatial distribution of actual motor movement. It turned out that the role of primary motor areas in the motor imagery is relatively large in the conditions of electrocortical stimulation with image-induced surface activity of the cerebral cortex. At the same time, the magnitude of imaging-induced cortical activity change was ~25% of the magnitude associated with the actual movement. Moreover, as the training and development of the control skill in the neural interface circuit in a simple feedback task, the changes in the motor imagery-related brain activity significantly increased, in some cases exceeding that with movement execution [24]. On the other hand, there is no unambiguous opinion in the literature how much the brain potentials recorded in the conditions of movement execution and motor imagery differ, and, in particular, there are indications [21-23] for their absence. The existing uncertainty prompts further investigation of this problem area.

Despite this, neurophysiology is steadily approaching the understanding of how motor (motor) and cognitive information is processed by populations of neurons and the brain as a whole [20, 25]. Based on the available experimental facts, well-known principles of frequency, temporal and population coding have been developed [26-28], however, exhaustive knowledge of the relevant mechanisms may not be required to create neural control systems. It may be sufficient to identify a correlation between neuronal activity and, for example, a person's intention to implement a corresponding movement or transition change in the functional state of the brain. Nevertheless, the request for the development and practical use of such systems significantly stimulated, for example, interest in understanding the nature of spontaneous and evoked electrical brain activity, adaptation mechanisms, mechanisms of perception and memory.

Finally, the widespread use of methods for analyzing and interpreting brain signals of an electroencephalogram (EEG) directly affects the reliability of the functioning of such a new brain-controlled channel, as well as the effectiveness of classifying patterns of electrical activity of the brain, ensuring the overall stability of the system [29]. These factors are still crucial for accelerating the spread of neural control technology, not only for research purposes, but also in the mass consumer market. BCI systems can be useful in solving problems of monitoring the functional state of a person, as well as the formation of a new non-muscular, auxiliary channel for controlling devices for various purposes.

4. Conclusions

Thus, it is shown that:

1. A complex and multidimensional EEG signal is successfully decomposed into independent components to improve the accuracy of developed classifying algorithms. The possibility of describing invariant EEG patterns of movement execution and motor imagery with a minimal set of feature spaces based on the analysis of the covariance matrix of vectors is also revealed.
2. There are significant differences between EEG phenomena that are formed in preparation to an actual movement and its motor imagery reproduction.
3. Eigenvectors of spatio-temporal EEG patterns associated with the movement execution and motor imagery-related brain activity can be used as markers for classification tasks, including in the framework of the neural network-based BCI approach.

Conflict of Interest

The authors declare that they have no conflict of interest.

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