Signal Processing of Motor Imagery EEG Waves Using Empirical Mode Decomposition

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Abstract Electroencephalogram (EEG) is the most convenient method for recording the electrical activities of the brain, for Brain Computer Interface (BCI) applications. This EEG data is notoriously noisy. A variety of frequency estimation techniques are used in feature extraction. This is possible due to the presence of information of interest in frequency bands which are well defined. The application of EMD (Empirical Mode Decomposition) on the recorded EEG waves of subjects', renders time-frequency data depicting instantaneous frequencies. EMD is chosen to obtain Hilbert–Huang Transform (HHT) of the data which is chosen over Fourier Transform (FT) owing to the nonstationarity, closely spaced frequency bands of interest and low SNR of the recorded data. HHT of the data can be used to obtain a feature or signature, which can be used as a command signal for various BCI applications.

Keywords EEG waves · Empirical mode decomposition · Fourier analysis
Hilbert huang transform

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1   Introduction

The cornerstone of BCI is the exclusive use of brain activity in computer-aided control. Neuroprosthetics and bioengineering are the major fields of BCI applications. EEG for brain activity recording is used widely due to its noninvasive nature, affordability and operation in real-time [1]. Motor imagery BCI being the imagination of motor action without actual physical movement, has clear practical significance [2]. This requires extended training periods, is challenging to analyse and has limited BCI channel capacity.

EEG research carried over more than seven decades has resulted in the introduction of an abundant class of quantitative feature extraction from EEG signals. Similar to any other signal, an elaborate mathematical model of the EEG signal is very promising [3]. Physiological findings and mathematical models correlating the EEG to electrical activities of a single nerve cell remain challenging and no mathematical model of EEG has yet achieved the aforementioned goal of modelling the wide varieties and dynamics of EEG. Autoregressive modelling of tiny EEG segments is successful to a certain extent [4]. The nonstationarity of EEG waves leads to the fact that mathematical models using static stationary equations are not suitable. Hence dynamic mathematical models have to be developed leading to increased complexity in the models.

1.1   *Nonstationarity in EEG Waves*

Transient events manifest themselves as the nonstationarity phenomenon of the EEG waves, such as alteration of homogeneous segments with dissimilar statistical features, spikes, sharp waves and spike-wave discharges. Visual inspection is sufficient for the identification of the transient behaviour owing to its specific patterns, but the identification of relatively homogeneous intervals requires theoretical basis [5].

The EEG data is converted to digital form to carry out the computer-aided analysis. The most of the prominent EEG components are present in the frequency range of 1 Hz to 30 Hz, hence the digitising rate is the range of 60 Hz–150 Hz [5]. Intervals which are less than 0.5–1 s need not be checked for stationarity if about, 50–100 samples are required for statistical characterization.

1.2   *EEG Waves Features*

The high frequency waves in the EEG data have been digitally removed by passing them through a Backman filter, low-pass filter with −67 dB at a 32 Hz cut-off. Later this filtered data is sampled at the rate of 64 Hz for feature extraction.

Table 1 Features of EEG waves

Parameter for extraction	Features	Symbols/Band
Time domain extraction	Statistical mean	X
	Sum of absolute amplitudes	$|X|$
	Sum of squared amplitudes	X^2
	Standard deviation	X_{cr}
	3rd moment of mean amplitude	m^3
	4th moment about the mean amplitude	m^4
	Skewness coefficient	g_1
	Kurtosis coefficient	g_2
Frequency domain spectral amplitude	$|A|$	0–32 Hz
	$|\beta|$	13–32 Hz
	$|\alpha|$	8–13 Hz
	$|\theta|$	4–8 Hz
	$|\delta|$	0–4 Hz
Frequency domain relative spectral amplitude	Alpha band	$\alpha\%$
	Alpha band	$\alpha\%$
	Beta band	$\beta\ \%$
	Theta band	$\theta\ \%$
	Delta band	$\delta\%$
Mean of frequency bands	Entire EEG spectrum	F_M
	Alpha band	F_α
	Beta band	F_β
	Theta band	F_θ
	Delta band	F_δ
Statistical analysis of frequency spectrum	Squared amplitudes	A^2
	Standard deviation	F_{SD}

Time, frequency and statistical tools are the approaches considered for extracting EEG waves features. From the sampled data 24 EEG signals are extracted, each with a window of 4 s. With this data the features listed in Table 1, can be extracted.

Fourier transform has been applied with a Hanning window on the EEG data to calculate the rest of the features. The following features comprising of the EEG waves spectral amplitudes are obtained. Using the same Fourier analysis, the relative spectral amplitudes of EEG, the mean frequencies, sum of squared amplitudes are thus obtained.

1.3 EEG Waves Feature Selection

Three standards are used to resolve the EEG features corresponding to behavioural alertness level. First, the EEG features having higher average rank across eight

procedures of data processing are mainly selected. The level of alertness is primarily manifested as the features with higher average rank numbers. Second, the EEG features with higher individual inconsistency are not selected as they have constrained use to the estimation of the level of alertness among subjects. The individual inconsistency is estimated using a measure called as Reliability Index (RI), which is given in Eq. 1.

$$RI = |N - P|/(N + P) \qquad (1)$$

where N/P is the corresponding addition of the ranks of negative/positive correlation coefficients across eight processing procedures or across different subjects. RI has a value in the range of 0–1. Features having higher RI values have lesser individual inconsistency with respect to the level of alertness. In the last standard, the interrelationships of EEG features are analysed to determine the redundancy of the EEG features in estimation of alertness. The addition of the ranks of negative/positive calculated in the previous standard is used here. Larger inter-correlation is obtained for higher values of overall sum of ranks. Finally, the EEG features having low individual inconsistency, lesser inter-correlation, larger correlation with alertness level are selected as consistent and effective factors for estimation of alertness level [5].

2 Experimentation

The proposed work is to find out the differences between the brain signals of different individuals, and to understand what makes them unique. The experimental setup for recording of EEG waves is as shown in Fig. 1. This uniqueness can be used as a password to a website/security system making it more robust [6].

So far, through the literature survey, the various methods currently existing for sensing EEG signals have been understood. In particular, techniques to record signals which are produced for a particular action. A protocol to capture brain signals has been developed, which:
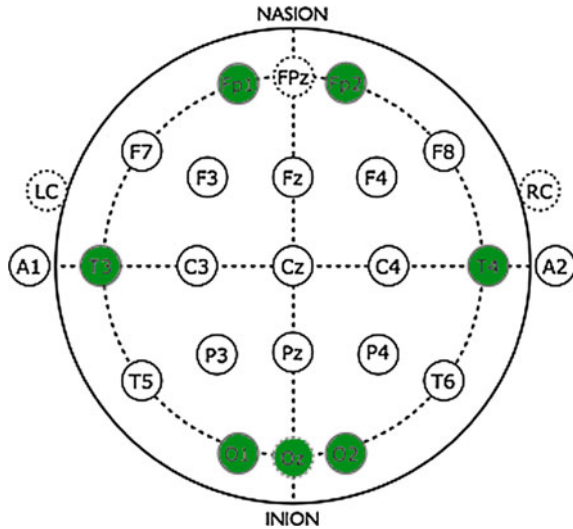

Fig. 1 Recording EEG waves of the subjects using enobio kit

Table 2 Specifications of the enobio device

| Parameter	Value
Total number of channels	8
Number of EEG records	18277
Number of packets lost	0
EEG sampling rate	500 samples/s
EEG units	nV

Fig. 2 Placement of the electrodes

1. Motor Imagery: The thought for the muscular movement is aided by a visual stimulus.
2. SSVEP: A protocol which uses images, which are flashed at the rate of 1 Hz, and provides visual stimulus to the subject.

The signals were captured using a device called Enobio. Enobio is a wireless technology which comes in three versions, 8, 16 and 32 channel electrode systems, used for collecting EEG signals. For the data collection, eightchannel electrode system was used. The complete device specification of the device is depicted in Table 2. The placement of electrodes on the subject is as shown in Fig. 2. In the Fig. 2, Green Dots indicate the placed EEG electrodes. Then, these signals were processed to retrieve information and points of interest. After filtering the signals, features must be extracted from them, and finally classified.

The placement of the electrodes mainly depends on the type of signal being analysed. The occipital lobe is responsible for the decoding of visual stimuli. Steady State Visual Evoked Potential (SSVEP) are usually recorded from occipital scalp for this reason. The channels which were used to collect VEP are Fp1, Fp2, O1, O2, Oz, T3 and T4 taking P3 as reference electrode. For Motor Imagery protocol, T3 and T4 are replaced by C3 and C4. The experimentation details are as shown in Table 3.

Table 3 Experimentation details

Parameter	Value
Number of subjects	8
Age	20–30
Number of trails on each subject	50
Duration of the protocol	30 s
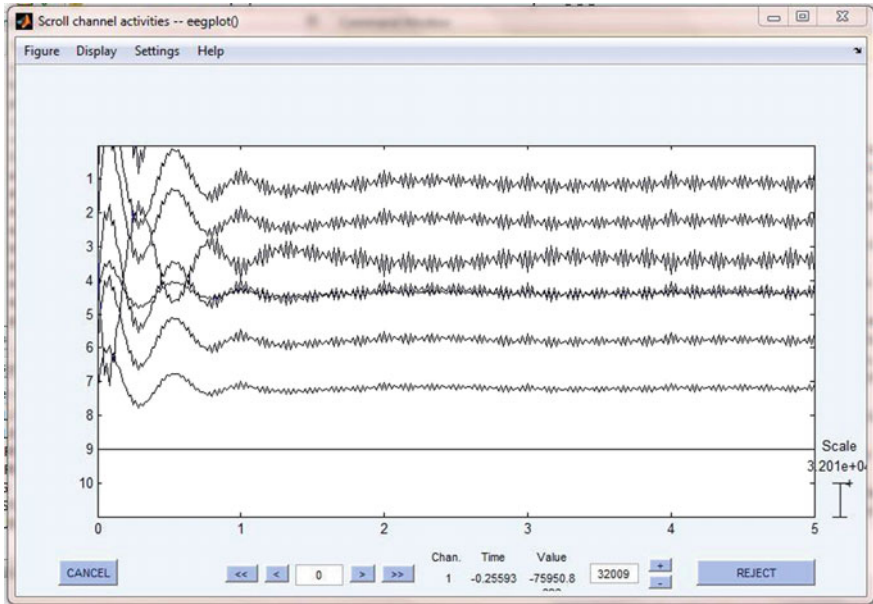
**Fig. 3** Time domain representation of the EEG waves of a subject

2.1 Time Domain EEG Waves of the Subjects

The EEG waves are recorded in time domain as shown in Fig. 3. The time domain EEG waves are stored in easy files. These files are processed using EEGLAB toolbox in MATLAB [7].

2.2 Power Spectral Density

The time domain signals are first filtered to remove various noises such as power line 50 Hz noise. Later EEGLAB provides tools to eliminate the mechanical disturbances from the eye movement and the blink rate. This processed time domain signal is then converted to its PSD format as depicted in Fig. 4.

Fig. 4 PSD of the EEG
waves of a subject
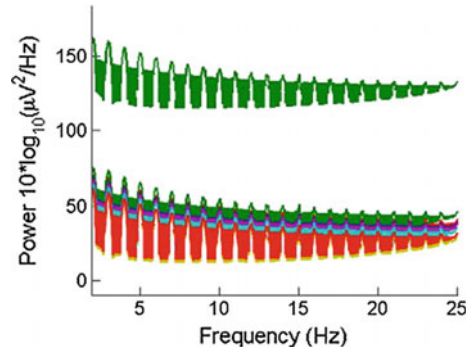
3   EEG Signal Processing

EEG Signal processing techniques comprise of time domain analysis, for digital
filtering and independent component analysis [8], frequency domain analysis, for
analyzing the spectrum, and time-frequency domain analysis.

3.1   Fourier Analysis for EEG Waves

EEG data is nonstationary, nonlinear and aperiodic by nature and Fourier Analysis
(FA) works best with stationary, linear and periodic signals. The local nonlinearity
of the data results in considerable spreading with the application of Fourier analysis,
as the basis functions of Fourier analysis are global. The dispersion is even higher
for data which significantly digress from the sinusoidal form. Thus the use of
Fourier analysis is not preferable for EEG.

3.2   Time-Frequency Domain Analysis for EEG Signals

The progression of a signal in frequency as well as time domain is described by the
time–frequency domain analysis. There are linear and nonlinear methods to carry
out this analysis. The linear methods being Short-time Fourier transform (STFT)
and Wavelet transform. The lone nonlinear method available is the Hilbert–Huang
Transform (HHT).

   The nonlinear nature of EEG waves makes HHT, the logical choice.

3.3   Hilbert Huang Transform

The instantaneous frequency data is obtained by the decomposition of the signals into Intrinsic Mode Functions (IMF) along with a general tendency of the signal and the HHT is way to do this. HHT is very suitable for data which is nonlinear and non-stationary [9]. Unlike Fourier Transform (FT), HHT is not a theoretical tool, but it is like an empirical or algorithmic approach that is very data-driven. Hilbert spectral analysis after the EMD (Empirical Mode Decomposition) are the two parts of HHT.

EMD is very efficient due to its adaptive nature. EMD is applicable to nonlinear and nonstationary processes as the method is based on local behaviour of data in the form of time series. Intrinsic Mode Functions (IMF) are the result of EMD which help in representing the data in time–frequency domain.

3.4   Empirical Mode Decomposition

The Hilbert spectral analysis is applied to IMF which is obtained by applying EMD to the data set.

IMF is more general as it not a simple harmonic function as in FT, but is a simple oscillatory mode. In FT the simple harmonic components have fixed frequency and amplitude, whereas in HHT the IMF has adaptive amplitude frequency which is dependent on local characteristics of the data [10].

Sifting is the process used to obtain the IMF. The process is carried as follows:

1. The cubic spline line connecting all the local maxima forms the upper envelope [7].
2. Lower envelope is formed by applying step 1 to the local minima [7].

All the data is sandwiched between the upper and lower envelopes. Their average is a1. The first component c1 is obtained by subtracting a1 from the data:

Ideally, c1 must obey the constraints imposed on IMF. This is taken care by the method used to construct c1 in the preceding step making it symmetric about 0 with maxima > 0 and minima < 0. After the initial round of sifting, a trough may become a local minimum.

The extrema obtained in the new rounds help in revealing the correct modes, which vanished in the prior rounds of examination. In the next rounds of sifting the component c1 is treated as data [10].

$$X(t) - a_1 = c_1 \tag{2}$$

With n times of recursive sifting, c_1 converts to an IMF, that is

$$c_1 - a_{11} = c_{11} \tag{3}$$

Table 4 Comparison between Fourier transform and Hilbert–Huang transform

Transform	FT	HHT using EMD
Operation	Convolution: uncertainty and global	Differentiation: certainty and local
Representation	Energy vs frequency	Energy vs time and frequency
Linearity condition for the data	Linear	Nonlinear
Stationarity condition for the data	Applicable for stationary data	Applicable for even non stationary data
Extraction of features	Not possible	Possible
Core concept	Derived from theory	Developed as an empirical method

Then, the component c_{1n} is chosen as the 1st IMF component of the data set:

$$c_{1(n-1)} - a_{1n} = c_{1n} \tag{4}$$

$$c_1 = c_{1n} \tag{5}$$

The above algorithm results in the decomposed EEG data providing the instantaneous frequency of the subject. This information can be utilised for various applications. Table 4 shows the comparison between Fast Fourier Transform (FFT) and Hilbert–Huang Transform (HHT). The results section deals with the consequences of these differences between the methods, on the suitability of the method to be chosen for data obtained from a particular protocol.

4 Results

The simulation results in this section are obtained using EEGLAB plugin [6] for MATLAB v15a. This section will summarise the results obtained for the two protocols, SSVEP and Motor Imagery. In the SSVEP protocol the images are flashed at a regular rate of 1 Hz. The FFT of a percentage of the data collected with SSVEP protocol for a particular subject is shown in Fig. 5. The two parts of Fig. 5 are the Event-Related Spectral Decomposition (ESRP) in dB and Inter-Trial Coherence (ITC) phase in rad. The Event-Related Potential (ERP) is also plotted. The events here refer to the flashing of images on the screen. The plots in Fig. 5 reveals that FFT is suitable for analysing the data obtained through SSVEP protocol as a regular pattern is observed in the FFT as well as the ERP's.

Figure 6 shows the FFT of the data obtained through motor imagery protocol. There is no regular pattern in ESRP, ITC phase or ERP's. This is because the data obtained through motor imagery is aperiodic data. Therefore, HHT is suitable. This is justified in Figs. 7 and 8. The Channel 12 corresponds to C3 and channel 13 corresponds to C4 in 10-20 International electrode placement system. These are the
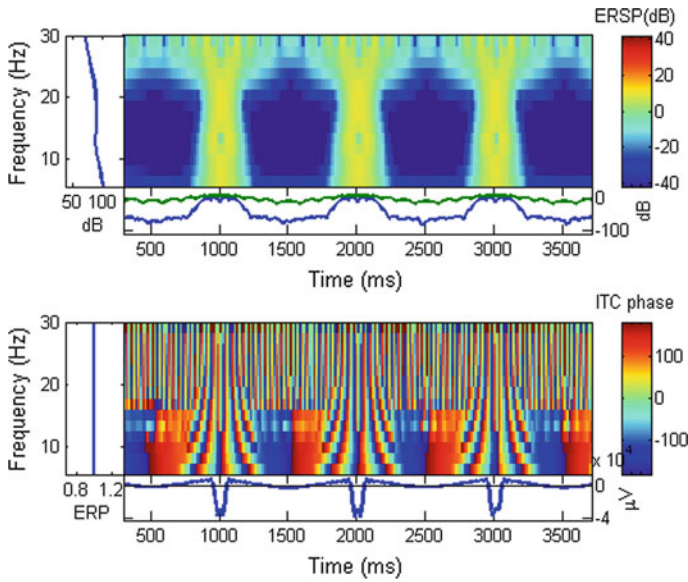
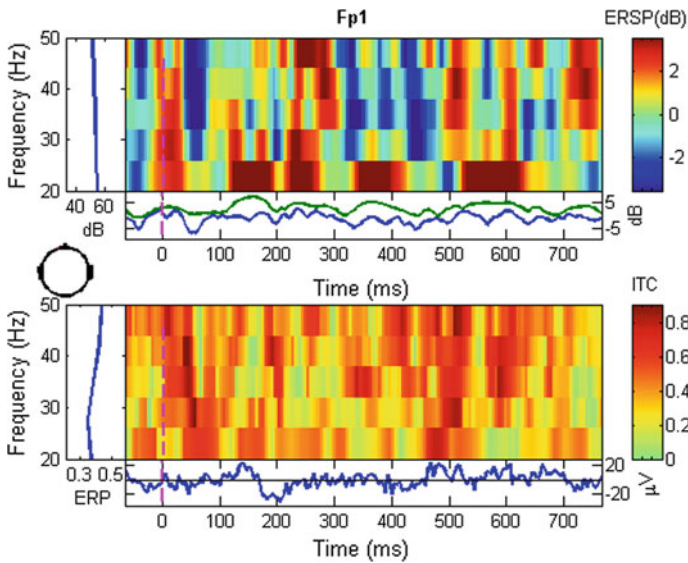**Fig. 5** FFT of steady state visual evoked potential data

Fig. 6 FFT of motor imagery EEG waves data

two channels in central lobe where the activity increases during motor imagery. Figures 7 and 8 correspond to the HHT of the data collected using motor imagery protocol. The motor imagery action performed in this case is the subject thinking
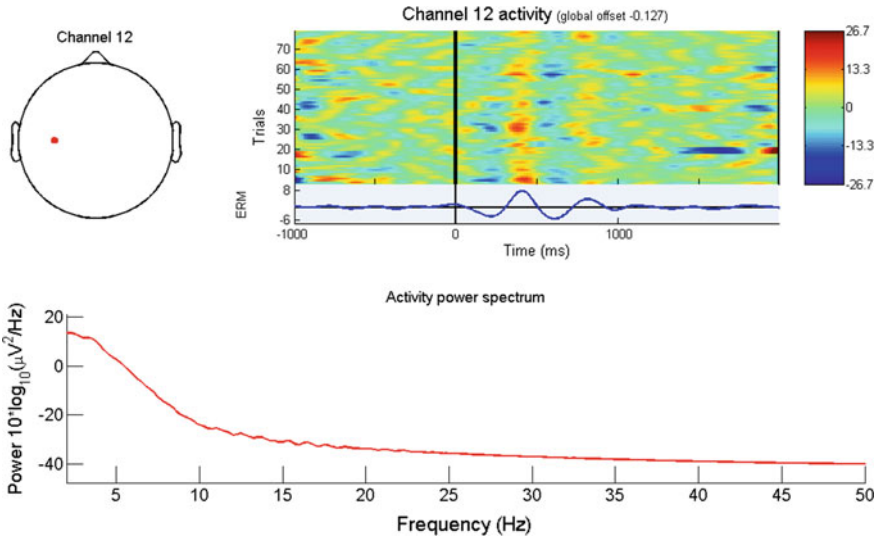
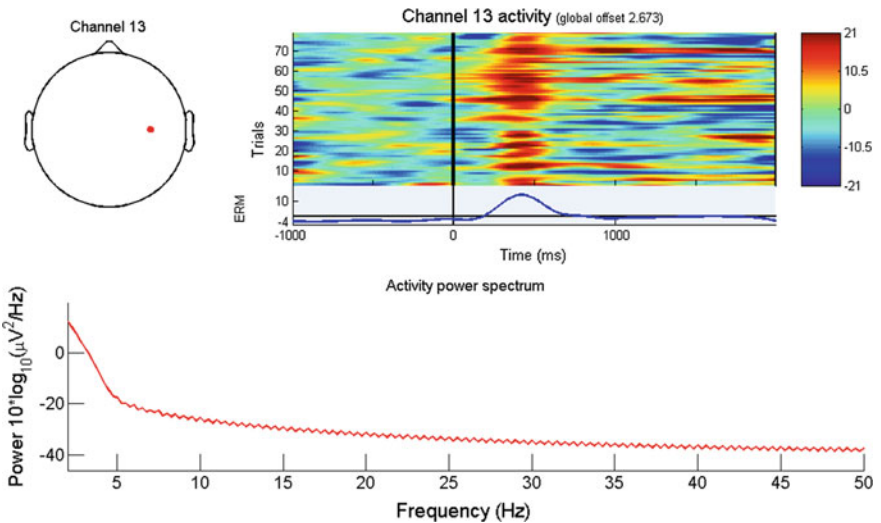**Fig. 7** Event related synchronisation (ERS) of C3

Fig. 8 Event related desynchronisation of C4

about moving right hand. The activity spectrum clearly shows the Event Related Synchronisation (ERS) of C3 in Fig. 7 and Event-Related Desynchronisation (ERD) of C4.

5 Conclusion

Development of any BCI application requires the features of EEG waves of the subject. The various EEG features have been enlisted in the proposed research work with their significance. The EEG data for the subjects have been extracted from the proposed protocol and the Enobio electrodes have been used to record the EEG waves of the subject. Later it has been proved that Fourier analysis is not entirely sufficient for the EEG waves feature extraction as the data is non-stationary, non-linear, and not periodic. Hilbert–Huang Transform is applied to the data to obtain the time–frequency joint and to extract the features. From the results it is evident that, for protocols such as motor imagery, HHT is the best suited protocol for feature extraction owing to its application on aperiodic data. FFT serves to give satisfactory results when applied to protocols like SSVEP owing to the periodic data generated by these protocols.

HHT of the data is obtained using Empirical Mode Decomposition algorithm which is a pragmatic approach to analyse non-stationary data sets, such as EEG waves data. EMD uses a heuristic approach for signal decomposition, which reduces the signal for a given locality with no restriction on conditions such as, sparseness, independence or orthogonality.

6 Future Work

The algorithm and the protocol used have been experimented with an 8-channel EEG electrode system to analyse motor imagery EEG waves, as compared to the 59 channel EEG electrode system used in [1]. Thus the proposed system is more economical and effective. The EEG waves corpus developed can be utilised for various embedded system applications such as, for human identification/security [8], controlling robots, etc. Motor imagery EEG waves processing can also be used to develop prosthetic arms/legs for physically challenged people. With the increase in number of EEG electrodes, the entire brain of a patient can be mapped, which would result in faster and efficient diagnosis.

Specifically, by improving the protocol and the correct placement of electrodes, diseases such as Alzheimer's disease, Dementia, Parkinson Diseases and many more can be diagnosed at their early stages. Also, diseases such as anaemia can also be detected using EEG waves by correlating it with the ECG waves. Since Brain waves control all the organs and systems of the human body, comprehending them can result in understanding the human body itself. Therefore, with a better understanding of the human body, the lives of the people can be enriched.

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