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An Adaptive P300 Model for Controlling a Humanoid Robot with Mind

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Abstract— **This paper presents a P300 model for controlling a humanoid robot with mind, including an off-line phase with a fixed trial number for training the model and an on-line phase with an adaptive strategy for generating commands to the humanoid robot.**

Our control scheme includes a procedure of acquiring P300 signals, topographical distribution analysis of P300 signals, and a classification approach to identifying subjects' mental activities regarding robot-walking behavior. Our study shows that the adaptive model is fast and practical to control humanoid robot via brainwaves.

I. Introduction

P300 is a kind of evoked potential which is a large positive deflection after the event being presented about 300ms [1]. This potential can be regarded as a degree index of the relevance between stimulus and subject's cognitive task [2]. This classical P300 Speller based on "oddball" paradigm first set up in [3] provides a new communication channel to identify subjects' mental activities by analyzing P300 signals. Since then, applications of P300 potentials have emerged, e.g., a P300 Speller for communication with computer [4], an internet browser for surfing [5], controlling a mouse on the screen based on both mu/beta and P300 potentials [6] or controlling an object in a virtual environment [7]. Significant attempts to control physical devices are reported, e.g., to navigate a wheelchair [8], and even to control a 7 degree of freedoms (DoFs) robotic arm mounted on a 2-DoFs wheelchair [9]. These applications become more and more interesting to disabled patients to help themselves in their daily life.

Control of a humanoid robot with mind is an emerging topic cross over multi-disciplinary areas, such as neuroscience, psychology, and robotics. A humanoid robot has the similar physical appearance and motions with people and is able to perform more complicated tasks for our daily life. It is very challenging to control a humanoid robot via brainwaves due to its high DOFs. The literature on this research topic is very limited. The paper [10] describes an asynchronous robot navigation system that allows the subject to control the humanoid robot to explore the environment with motor imagery. Bryan *et al*. [11]propose an adaptive BCI interface for semi-autonomously controlling a robot. The paper [12] uses a SSVEP model (steady-state visually evoked potentials) and a task-function to control some robot tasks. The work in [13] uses P300 evoked potentials to control a humanoid robot to target a selected object in a captured image. When a subject focuses only on the flashing border of the selected target, the robot acts to pick up the target according to the pre-knowledge of a given environment. In addition, this work lacks a detail report on the procedure of acquiring P300 brainwaves and how to achieve the high quality of brain signals.

Controlling a humanoid robot with mind according to the current robot status and the environment information, a feedback is essential in such a brainwave-based closed control system. In work [14], we use Cerebot, a mind-controlled humanoid robot platform [15], [16], to investigate a P300 model for control of a NAO robot, as shown in Fig. 1. We develop an OpenViBE-based experimental environment, which integrates OpenGL, OpenCV, WEBOTS, Choregraph, and Cerebus signal acquisition software [17]. We design two groups of image contexts to visually stimulate subjects when acquiring neural signals that are used to control a simulated or real NAO robot. Our study shows that the group of contexts using images of robot behavior delivers better performance. Following-up our previous report, this paper presents an adaptive P300 model for controlling a humanoid robot with mind to improve control performance.

This paper is organized as follows: Section II discusses the P300 model-based control scheme and briefly presents the OpenViBE-based programming environment. Section III describes the detail of our experiment procedure and introduces the proposed adaptive P300 model. Section IV

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discusses the features of acquired P300 brain signals. Section V controls a humanoid robot via brainwaves. Section VI draws conclusions on the P300 model for control of a humanoid robot.

II. P300-BASED CONTROL SCHEME

A. Cerebot

Cerebot is a mind-controlled humanoid robot platform [15], [16], consisting of a Cerebus™ Data Acquisition System, a humanoid robot, and a virtual simulator WEBOTS, as shown in Fig. 1. Cerebus™ is a neural signal acquisition system, including an amplifier, an amplifier power supply, and a neural signal processor. This system is capable of recording from both surface and extracellular microelectrodes until 128 channels and provides several on-line processing options for neural signals including noise cancellation, adjustable digital filters, simultaneous extraction of spike and field potential recordings from microelectrodes, and automatic/manual online spike classification. The Cerebot platform uses Cerebus™ to record brainwaves during human mental activities. This platform uses a NAO robot with 25 DoFs shown in Fig. 1 or a KT-X PC humanoid robot with 20 DoFs shown in Fig. 2. Both types of humanoid robots are equipped with speakers, a camera, 3 axis gyro/accelerometer chips, and wireless connection adaptors. The robots can be controlled in real-time or based on predefined behaviors in C++ or Python.

B. P300 Model

In this study, we investigate the adaptive P300 model for control of a NAO robot. A classical P300-based system can be divided into three parts: signal acquiring, signal processing and classification, and robot control. In the first part, a subject should regard one of the visual stimuli as a target and attend on it when it changes (such as flash, change appearance) randomly. The stimulus change is uncertain to the subject, and the target flash elicits P300 signals. The P300 evoked potentials are prominent in parietal and occipital electrodes, such as the channels Pz, Fz, Cz, and Oz, but their amplitudes are just about 5-15uV which may be drown in background noises, so these neural signals need to be pre-processed by a bandpass filter to remove noises. A visual stimulus activates a window with a width of about 0.5-0.8s to catch a P300 potential at the selected channels that usually appears after 0.2-0.8s of stimulus. The window repeatedly catches P300 signals for several times and a classification approach averages epochs in the window to construct a feature vector. Many classifiers, such as LDA, SVM, and Neural Network, can judge whether an epoch contains a P300 potential or not. The classified P300 signals evoked by their visual stimuli that represent robot-walking behavior are transformed to corresponding commands to control the NAO robot. In practice, after a command being sent, there is a short pause for the subject as the robot needs this short period to complete the action and to stay back the state of waiting for the next command. For a given task, the subject decides which stimulus to attend on in the next trial, based on a pre-defined action order or the robot current status and the feedback information of environment.

C. OpenViBE Programming Environment

OpenViBE is new general-purpose software for designing, testing, and using brain-computer interface. It includes many functional boxes, such as real time signal processing, signal visualization, matlab/lua script, and communication box that links OpenViBE and other exactable files. Using OpenViBE, it is easy and fast to design a brain-computer interface in an intuitive way, as it is a visual programming language that provides a number of powerful toolboxes. Each of the tools comes as a plug-in to communicate with an application via a generic interface hiding implementation details. Fig. 1 describes the OpenViBE programming environment for the Cerebot platform. The environment integrates the visual stimulus section, collecting signal section, signal processing, classification section, and robot control section. The stimulus section displays a designed image context to the subject and synchronously sends a stimulus label that is related to the flashing to the Cerebus™ data acquisition system. The signal processing and classification section analyzes the P300 signals using a matlab script box in OpenViBE and transfers the classification result to a control command of the robot.

III. EXPERIMENT PREPARATION AND PROCEDURE

A. Experimental Protocol

The experiment design is based on the classical “oddball” paradigm. An OpenGL-based module displays a 2*3 matrix with contexts on the screen. Each robot image in the matrix represents a robot walking behavior: walking forward, walking backward, shifting left, shifting right, turning left, and turning right, as shown in Fig. 2(b). The image resolution is 120*120 pix. The distance between the centers of two images in a row is half-length of the screen, and in a column is 0.4 times of the width of the screen. The screen background is set as grey. When one robot image is flashing, the others will be shielded by an “off image.” That is, if one of the six robot images is chosen as a target, the other image contexts stay in standard stimulus [18]called non-targets in our study, and the probability of flashing a target is 1/6 (the probability is the

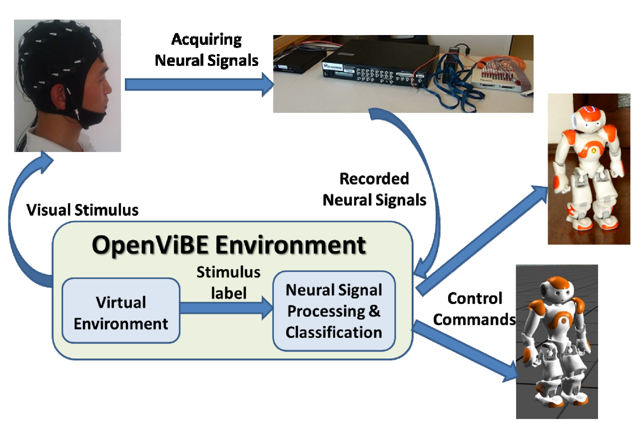
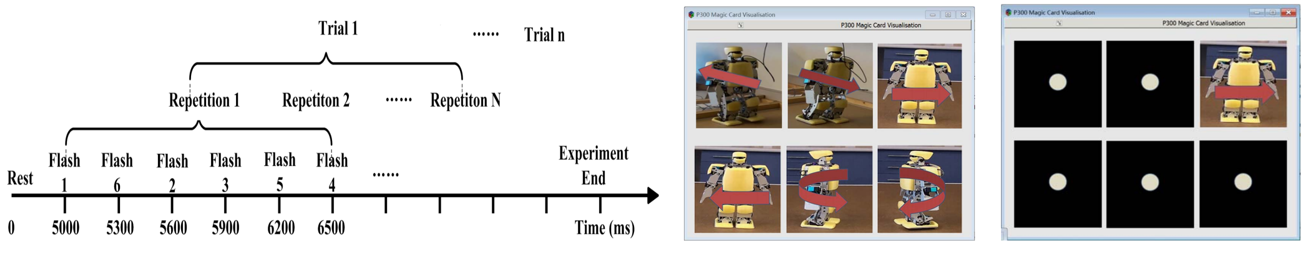


Fig. 1. Cerebot, a mind-controlled humanoid robot platform.



(a) (b) (c)

Fig. 2. (a) The protocol of P300 model. (b) Before the experiment, six images with different contexts are shown to the subject so that the subject understands their meanings. (c) The interface of image flashings in an experiment. (Note: in order to see the images clearly in paper, here the images size increases and the distances of images' locations decrease.)

reciprocal of the number of images) which meets the requirement of eliciting P300 potentials [19]. The context of an "off image" is a black square with a white solid circle located in the middle of the image, as shown Fig. 2(c). Our experiments show that these circles are important for the subject to prevent distraction during the time gap between two targets flashing on the screen.

When an experiment starts, the screen is blanked in grey color for 5 seconds, and then six robot images flash separately once in a random order called as "repetition." The presentation time of an image lasts for 200ms and the interstimulus interval (ISI) [20] is about 300ms, so a display cycle of a repetition is 1.8s shown in Fig. 2(a). A trial consists of several repetitions in which the subject is asked to focus on only one robot image, which means that each robot image flashes several times before the P300 model outputs a command to control the humanoid robot. Usually, in a traditional P300 model, a number of repetitions are fixed in a trial, e.g., 12 repetitions are set in this paper. The adaptive P300 model proposed herein automatically determines the number of repetitions based on the subject's mental state. The subject is suggested to count number when a target image presents and to do his/her best to ignore the other robot images flashing.

B. *Experimental Procedure*

Before starting experiments, the subject needs to be wearing an EEG cap manufactured according to "the international 10-20 system" (a 32-channel EEG, or a 64-channel or a 128 channel cap is available for our experiments). The channel Cz is first put on the subject's vertex, and then the other channels are correctly placed according to the location of Cz. The ground electrode is AFz and the linked-mastoids are references. Elefix conductive paste diluted with water in a proportion of 5:1 is injected to the surface of scalp by a syringe which sticks the electrodes on the skin for its low impedance and highly conductivity. The diameter of the needle tubing is 3mm which is little less than the diameter of the hole of the electrode. Before the experiment, the brain signals will be watched for a while in order to check whether the signals are affected by some factors, such as line noise, and poor connectivity between scalp and electrodes.

The subject sits in a comfortable chair. The distance from the subject to the display screen is about 70cm and the subject's eyes are at the same horizontal level with the screen center. The screen size is 22 inch and its resolution is 1440*900 pix. The subject tries to avoid doing any motion during acquiring P300 signals. A complete experiment is conducted in a silent environment.

C. *Classifier*

When a trial is completed, the signal analysis section provides six averaged epochs corresponding to their image contexts at a selected channel. The classification section uses Fisher's Linear Discriminant Analysis (LDA) to classify P300 signals. A two-class classification algorithm classifies if a P300 potential is elicited under the target condition or not. This technique is to find a good direction in which the projection of the same class are tightly grouped, but well separated from the other class [21], and to determine a threshold for comparing the projection of features. First, the classification section determines the dimension of a feature vector extracted from an averaged epoch. Because the length of the average epoch is 500ms and the sampling frequency is 1000, the dimension of a feature vector is 0.5*1000/10=50 in which the sampled signal data in the epoch are decimated by a factor of 10. The feature vectors of the averaged epochs are inputs to the classifier and are projected to the direction, and the outputs of this classifier are scalar values. If a value is larger than the threshold, it is labeled as "target;" otherwise it is labeled as "non-target." The feature vector from each trial is classified in this way. When a trial is completed, the features corresponding to the six image contexts are input to the classifier. If more than one feature are labeled as targets, we choose the one with the largest scalar value as the target. Therefore, the classification part is an integration of the LDA classifier and a select mechanism. A final result is transformed into a command for control of the humanoid robot to actuate a walking behavior according to its image context labeled as the target.

D. *Adaptive Model*

Our studies show that a better feature of P300 signals can be achieved when the number of repetitions in a trial is larger. However, increasing the number of repetitions slows down the response of the P300 model because a latency of P300 is nearly a constant. To tackle this problem, we propose the adaptive P300 model for controlling a humanoid robot. This model links the number of repetitions during the on-line control phase with subject's mental state [22].

For the adaptive model, the training phase remains unchanged, as the model needs enough repetitions to collect good data for training the classifier and this off-line process does not affect an on-line control response. In the on-line control phase, an adaptive strategy is proposed as follows. We set a minimum and maximum number of repetitions in a trial (separately denoted as M1 and M2) and the number of total repetitions in a trial is defined as N. In a trial, the repetitions should be repeated at least M1 times to activate the classification section. When the classifier can determine a target after N times of repetitions (M1≤N≤M2), the model stops the trial and begins a new trial after a break of 5 seconds. If no target is judged after M2 times of repetitions, the model declares that the subject doesn't produce a P300 signals in this trial and the model precedes the next trial. Thus, for the adaptive model whether the trial is continued is dependent on the mental state. If the subject can concentrate well in the trial, his or her P300 signals are obvious and a recognizable target feature vector is formed from fewer repetitions. The flow-process diagram in Fig. 3 shows the principle of the adaptive P300 model.

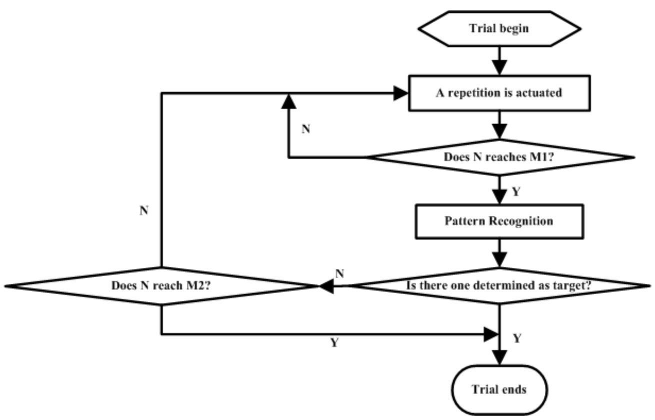


Fig. 3. Flow-process diagram of the adaptive P300 model.

IV. Signal Analyses

The acquired neural signals is amplified, preprocessed by an analog low-pass filter of 50 Hz, and digitalized with a sampling frequency of 1000Hz. Then, a digital band-pass filter with the bandwidth of 0.5 to 26Hz filters the neural signals. The epoch in which the maximum amplitude is higher than 90uV is removed and the left epochs are subtracted by a baseline that is the average of the signal data within a window of 300ms before a stimulus flashing. As the P300 signals in central and parietal part are relative prominent according to the theory about P300 [18], the signals collected from channel Pz are plotted in Fig. 4(a). The blue and red solid curves represent the averaged signals under target and non-target stimulus conditions. The amplitude of blue line is much larger than the red one at about 340ms, which indicates that this protocol elicits P300 potentials. The signed r^2 function is an index to describe the discrimination between the signals acquired under two different conditions. Assume that there are N_k values $x_i^{(k)}$ measured under condition k

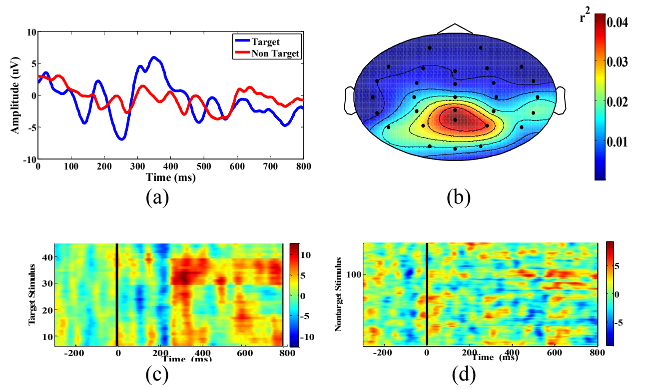


Fig. 4. (a) Averaged brain signals at the channel Pz under target/non-target conditions (N=45). (b) The r^2 value distribution. (c) Neural signals elicited under target stimuli. (d) Neural signals acquired under non-target stimulus.

$(k=1,2; i=1,2,\cdots,N_k)$, then a two-dimensional data set is constructed. The points (x, y) in the data set can be divided to two kinds: $(x_i^1, 1)$ or $(x_j^2, \text{-}1)$, $(i=1,\cdots,N_1; j=1,\cdots,N_2)$. Then the equation of signed r^2 is below:

$$r^2 = \frac{\mathrm{cov}(x, y)}{\mathrm{var}(x) * \mathrm{var}(y)}, \qquad (1)$$

where $\mathrm{cov}(x, y)$ is the covariance of two vectors, and $\mathrm{var}(x)$ is the variance of a vector. Larger the value is, more obvious the difference between two conditions is. Fig. 4 (b) shows the r^2 values' topography distribution over all channels. The color bar on the right shows the r^2 value range. Dark red represents highest r^2 value and the value decreases when the color changes from dark red to dark blue. The r^2 values around the channels Pz and Cz are the highest and become lower when other channels' distances increase from these two channels, as shown in Fig. 4(b), so it is assured that the target stimulus causes biggest change in the parietal and occipital area. It is also important to investigate the amplitudes of neural signals after each visual stimulus. The color bars in the second row represent the value of amplitude, and the n axis is the index of stimulus. A color spot (t, n) in Fig. 4 (c) or (d) represents a value of the signal elicited by nth stimulus flashing at t ms. As shown in Fig. 4(c), some red spots mainly appear between 200 and 400ms, which indicates that there are positive deflections during this time period after target stimulus flashings. As the neural signals under the target condition exhibit the features with their peaks at about 340ms as show in Fig. 4(c), it is assured that this experiment procedure elicits P300 potentials; whereas, as shown in Fig. 4(d), the neural signals under the non-target condition look unexciting because the color points appear randomly after stimulus flashings and the signals amplitudes are relative low.

V. NAO Robot Control Test

A. Introduction of Evaluation

This section describes an evaluation of the P300 model by control of a simulated or a real NAO robot. It is important for the subject to attend on the stimulus during each set of the experiments. As shown in Fig. 1, the signal processing, classification, and control sections are integrated into the

OpenViBE-based environment. The testing part is divided into two parts: the part of off-line testing and the part of on-line controlling. In the off-line testing part, the test data that are processed and classified as described in previous section are used to count the accuracy of the traditional and adaptive model. In the on-line controlling part, we apply the adaptive model to control the simulated or real NAO robot. The video clip on control of the NAO robot walking behavior using the P300 model is available on the website http://v.youku.com/v_show/id_XNjAzNjE3Njc2.html.

B. *Off-line Testing of Traditional and Adaptive Model*

Two right-handed, a male (Subject One) and a female subject (Subject Two) with normal vision are volunteers to undergo the experiments. The collected neural signals are divided into the training and testing data for the LDA classifier. In order to evaluate the P300 model objectively, the collected signals are randomly chosen to train the LDA classifier, and then the remaining part of the collected signals are the test data for testing the LDA classifier. The evaluation process of P300 model repeats the procedure for training and testing the LDA classifier using the same data. The success rates of evaluating the P300 model are the averaged values of all iterations of training and testing outcomes based on the collected neural signals. In the experiments, Subject One did 48 trials, and Subject Two did 72 trials. As discussed above, data of 36 trials of the neural signals collected from each subject are randomly chosen to train the LDA classifier, and then the 12 remaining trials of Subject One and 36 remaining trials of Subject Two are used to evaluate the P300 model. For Subject One, the evaluation process repeats 4 times; whereas for Subject Two, the process does 6 times.

For the evaluations of the traditional P300 model, the neural signals collected at the channels Pz and Cz are separately used to construct feature vectors and the number of the repetition is fixed to 12. Table I lists the accuracy rates of P300 evoked potentials. We summarize the evaluation results as follows. For Subject One, the success rate is over 85.00%. For Subject Two, the success rate is over 97.00%. In the experiments, the success rate of Subject Two is higher than these of Subject One. The reason might be that Subject Two gets already familiar with the P300 experimental procedure. In addition, the higher success rates for the two subjects appear at different channels because of individual differences.

TABLE I
ACCURACY RATES OF P300 EVOKED POTENTIALS

Subject	Channel	Accuracy
One	Cz	87.49%
One	Pz	85.39%
Two	Cz	97.22%
Two	Pz	97.69%

In the adaptive P300 model, the number of repetition is adaptive to the subject's mental state. The M1 is ranged from 1 to 8, and the M2 is set 12 which is the same with the fixed number in traditional model. We count the accuracies as M1 changes, and find that the accuracy increases with M1 increases. Here is Fig. 5 which shows the trend of accuracy of Subject Two. In the general case, the real number of repetition in an experiment is the same or little bigger than M1. So from this Fig. 5, we can see that when the repetition repeats three or four times, the accuracy reaches 95% which is relative high. And the time of 3-times repetitions is just 5.4 seconds, so an interval between two commands is just 10.4s. Compared with the time of traditional model 26.6s, the speed is improved about 2.6 times.

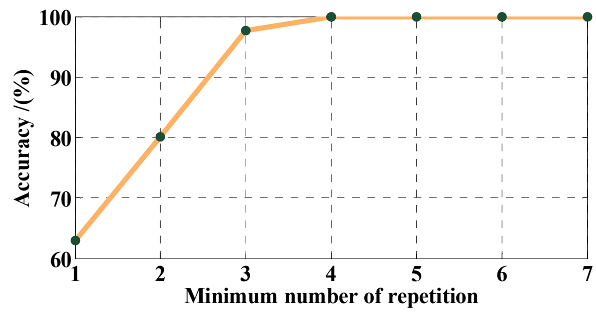


Fig. 5. Accuracy of adaptive model with different M1.

C. *On-line Testing of Adaptive Model*

We also implement the adaptive P300 model on the Cerebot platform to control a NAO robot. In each trial, the subject is instructed by an operation staff to focus on an image of which the context is the target behavior of the robot. A visual stimulus elicits the P300 potential, and the signal process and classification section processes and converts the potential into a command for control of the robot. When a trial is finished, there is 5s for the subject to rest, and then a new trial begins. The subject doesn't know the target image beforehand or the number of repetitions in each trial. Subject Two does totally 90 trials in which M1 is set 3. One trial is abandoned as the subject doesn't catch the order of the operation staff. In other 89 trials, the robot does right 78 times. The accuracy (87.6%) is lower than the off-line result; the reason for it is probably that the subject's state is affected by the robot's actions as she sometimes diverts her attention on the robot's situation. Fig. 6 displays two behaviors of the robot.

VI. CONCLUSIONS

In this paper, we use Cerebot to investigate the adaptive P300 model for control of a humanoid robot. The experiment procedure is designed to meet the demand of eliciting P300: low probability, uncertainty of target stimulus and relation with subject's attention. The analysis results on the amplitude, latency and polarity of the acquired neural signals that are elicited after flashing a target demonstrate that the experiment protocol is able to elicit the P300 potential well. However, low bandwidth of a P300 model and easy fatigue for subjects when they are doing some complex task are the main disadvantages of the traditional P300 model. For the first disadvantage, we propose an adaptive model that makes the experiment process adaptive to subject's mental state. In this way, both the accuracy and speed are improved.

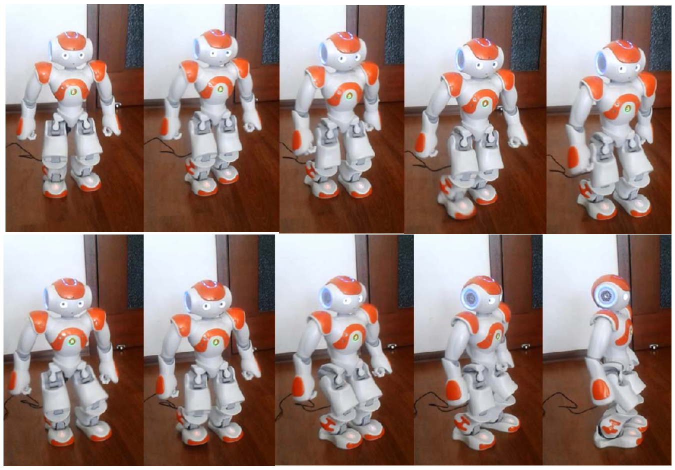


Fig. 6. Nao robot walking behaviors: the photos in the first row show the robot walking forward and in the second row show robot turning left.

Our future research will investigate the behavior imagination-based on model for control of the humanoid robot that relies less on the visual stimulus [15], [16], because we think this model may reduce the visual fatigue caused by continuous images flashing. Also, to make a mind control system practical, we still need to develop some other adaptive models to improve both the accuracy and speed.

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