Mimetic Communication Theory for Humanoid Robots Interacting with Humans

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Summary. The theory of behavioral communication for humanoid robots that interact with humans is discussed in this paper. For behavioral communication, it is fundamental for a humanoid robot to recognize the meaning of the whole body motion of a human. According to the previous works, it can be done in the symbolic level by adopting the proto-symbol space defined by the Hidden Markov Models based on the mimesis theory. The generation of robot motions from the proto-symbols is also to be done in the same framework. In this paper, we first introduce the meta proto-symbols that stochastically represent and become signifiants of the interaction of a robot and a human. The meta proto-symbols are a little more abstract analogy of the proto-symbols and recognize/generate the relationship of the two. A hypothesis is then proposed as the principle of fundamental communication. The experimental result follows.

Key words: Mimetic Communication, Humanoid Robot, Human Robot Interaction, Mimesis Theory, Proto Symbol Space, Hidden Markov Model.

1 Introduction

Communication is defined as a process of information exchange between social creatures through common systems such as gestures, signs, symbols or languages. Gesture or behavioral communication has much longer history than that of language for the human beings. Mimesis hypothesis suggests that the humans started the use of signs and symbols in communication through behavioral imitation [1]. The importance of behavioral communication lies in the fact that it always stays behind and enables physical interactions between two humans.

The link between a sender and receiver of messages is a necessary condition for any communication [2]. The discovery of mirror neurons [3] [4] was an epoch-making event in neuroscience. The mirror systems enabled the link between a subject and the others through gesture messages. Namely, the mirror systems are related to the development of communication [5].

In this paper, we focus on behavioral communication to support interactions between humanoid robots and humans. We discuss the fundamental theory of behavioral communication for humanoid robots that interact with humans. For behavioral communication, it is essential for a humanoid robot to recognize the meaning of the whole body motion of a human. According to the previous works [6]-[9], it can be done in the symbolic level by adopting the proto-symbol space defined by the Hidden Markov Models based on the mimesis theory. The generation of robot motions from the proto-symbols is also to be done in the same framework.

We first introduce the meta proto-symbols that stochastically represent and become signifiants of the interaction of a robot and a human. The meta proto-symbols are a little more abstract analogy of the proto-symbols and recognize/generate the relationship of the two. A hypothesis is then proposed as the principle of fundamental communication. Namely, the communication is to recognize the relationship of the two and try to maintain it, whether it is cooperative or competitive. Technical implementation of the hypothesis can be done by simply short-circuiting the output of recognition and the input of generation of the meta-proto-symbols. The experimental result follows using a 20 DOF small-size humanoid robot, UT-μ2 magnum [18].

For interaction between robots and humans, Canamero et al [10] discussed the interface of humanoid robot named Feelix that showed various kinds of facial expression in response to touch stimulus from a human. Breazeal [11] studied a model of social interaction between an infant and a caretaker, and then developed a robot named Kismet with the social model. Imitation learning is also an active field of robotics research and various kinds of approaches have been presented [12]. Samejima et al [13] [14] reported that a two-link robot could symbolize, recognize motion patterns using predicting modules, and generate motion patterns using controlling modules. Morimoto et al [15] proposed a hierarchical reinforcement learning in order to acquire motion dynamics. Not many works have been done to bridge communication and imitation learning. Billard et al [16] presented a very interesting approach to acquisition of communication skill based on the child-mother model of imitation learning. This architecture was named DRAMA, the general control Dynamic Recurrent Associate Memory Architecture [17].

2 Mimetic Communication Model of Interaction

The proto symbol space [9] [8] is a vector space approximately structured for the set of the Hidden Markov Models. A HMM is acquired from a motion pattern and to be used to recognize and generate it. In the proto symbol space, we can handle continuous transition of motion patterns. Fig.1 shows the image of bidirectional computation using the HMMs.

The recognition of transition of motion patterns or the generation of motion pattern that smoothly changes from one motion pattern to another is

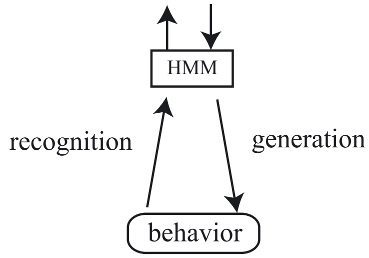

Fig. 1. Proto symbol space. Stochastic parameters of Hidden Markov Models are used for bidirectional computation of recognition and generation of motion patterns.

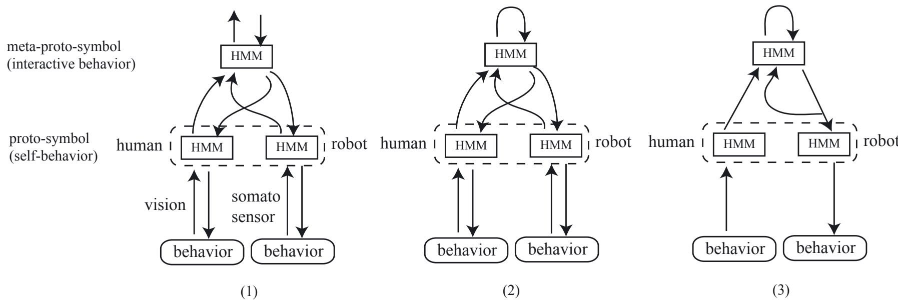

Fig. 2. Mimetic communication. A behavioral communication model for robots interacting with humans.

represented as a moving point in the proto symbol space. For the motion patterns of the point, we can define the second proto symbol space, which is called the meta proto symbol space since it represents the motion patterns of symbols.

In this paper, we propose to use the meta proto symbol space to represent the communication/interaction between a robot and a human or between the self and the partner.

Fig..2 explains the principle of mimetic communication model for interaction proposed using the meta proto symbol space.

In Fig..2 (1), a proto symbol space executes bidirectional computation of the self (robot) as well as that of the partner (human) of interaction. A meta proto symbol space is set in the second hierarchy and takes the sequences of proto symbols of the self and the partner as its behavior and executes bidirectional computation. The two recognition outputs of the self and the partner from the ptoto symbol space become the recognition input of the meta proto symbol space. The generation output of the meta proto symbol space separates into two and become the generation inputs of the proto symbol space. The recognition output of the meta proto symbol space implies for the self (robot) the estimated state of interaction, while the generation input of the meta proto symbol space implies the control strategy for the interaction. The essence of interaction is in the process of computing the control strategy from the estimated states of interaction. The process should vary and be designed depending on whether the interaction is purposeful, emotional, contingent, or naturally drifting.

A hypothesis for designing fundamental interaction, namely naturally drifting interaction is to short-circuit the recognition output and the generation input of the meta proto symbol space as shown in Fig..2 (2). Because the naturally drifting interaction can be modeled to estimate the states of interaction and attempt to maintain and generate the states. Note that the naturally drifting interaction model can represent not only cooperative or friendly interactions, but also competitive or hostile interactions..

The technical implementation was done in the form of Fig..2 (3) by eliminating generation processes of the partner (human) and approximating recognition processes of the self (robot).

3 General Algorithms of Recognition and Generation

3.1 Computational Problems

For both the proto symbol space and the meta proto symbol space, the computational problems are common. In the literature [9] the computation of recognition and generation were discussed in the simplest case, namely, as an interpolation between two proto symbols. The norm of the vector space was defined by the Kullback-Leibler information modified to satisfy the symmetry property. The proto symbol space was then constructed through the multi dimensional scaling.

For the continuous recognition of motion patterns, we use stepwise moving recognition. Fig.3 shows the stepwise moving recognition for the meta proto symbol space, where W_{span} is the time width of the moving window, and W_{step} is the moving time step of the window.

3.2 Motion Recognition

We represent the observation through the moving window by $\boldsymbol{O}^i(t)$ where $i = \{H, R\}$ is used to indicate human (H) and robot (R). Then, $P(\boldsymbol{O}^i(t)|\lambda_j)$ shows the likelihood that observation $\boldsymbol{O}^i(t)$ is generated by the proto symbol j.

Motion recognition is to find the coordinates in the proto symbol space that is appropriate for the observation. We propose the single Gaussian model for motion recognition as shown in Fig.4. We define a Gaussian that has value $P(\boldsymbol{O}^i(t)|\lambda_j)$ at the coordinates of proto symbol j of i, $\boldsymbol{x}_{\mathcal{PS}}{}^i_j$. The mean vector, $\boldsymbol{\mu}^i(t)$, and the covariance matrix, $\boldsymbol{\Sigma}^i(t)$, of the Gaussian are computed as follows:

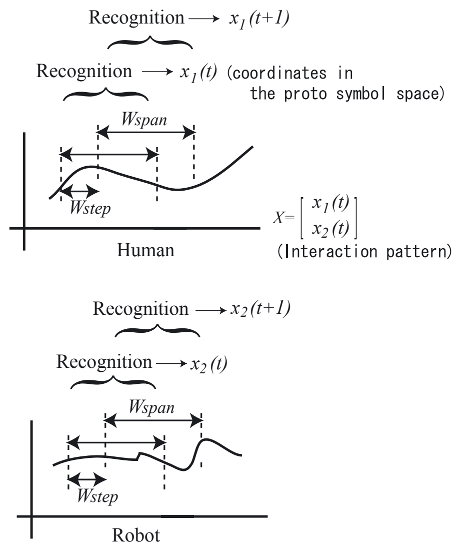

Fig. 3. Procedure for recognition of motion patterns

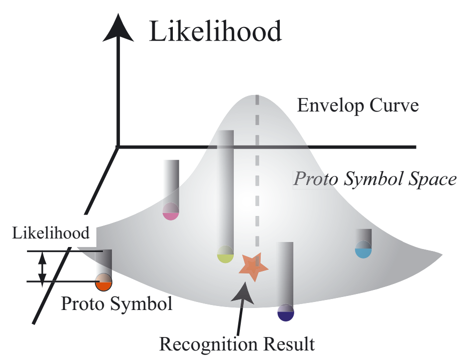

Fig. 4. The single Gaussian model for motion recognition.

$$\boldsymbol{\mu}^i(t) = \frac{1}{N_{\mathcal{PS}}{}^i} \sum_{j=1}^{N_{\mathcal{PS}}{}^i} P(\boldsymbol{O}^i(t)|\lambda_j) \boldsymbol{x}_{\mathcal{PS}}{}^i_j \tag{1}$$

$$\boldsymbol{\Sigma}^i(t) = \frac{1}{N_{\mathcal{PS}}{}^i} \sum_{j=1}^{N_{\mathcal{PS}}{}^i} \left(\boldsymbol{x}_{\mathcal{PS}}{}^i_j - \boldsymbol{\mu}^i(t)\right) \left(\boldsymbol{x}_{\mathcal{PS}}{}^i_j - \boldsymbol{\mu}^i(t)\right)^T \tag{2}$$

where $N_{\mathcal{PS}}{}^i$ is the number of proto symbols. The coordinates for the observation is given by $\boldsymbol{x}^i(t) = \boldsymbol{\mu}^i(t)$.

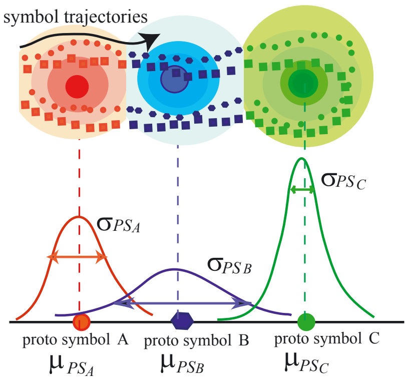

Fig. 5. Image of clustering analysis for compensating the sparseness of the proto symbols.

3.3 Likelihood of a Point in the Space

Computation of likelihood for observation is done in the previous subsection. We also need computation of likelihood of a point in the proto symbol space being associated with a proto symbol. This computation will be used for motion generation. The proto symbols are rather sparse in the proto symbol space and cannot provide a meaningful likelihood for a point distant from them.

We apply cluster analysis for the history of observations and use the result to compensate the sparseness of the proto symbols. For each observation $\boldsymbol{O}^i(t)$, we have a point in the proto symbol space, $\boldsymbol{x}^i(t) = \boldsymbol{\mu}^i(t)$. We also compute the proto symbol that provides the maximum likelihood. Namely,

$$\mathcal{R}^i = \arg\max_j P(\boldsymbol{O}^i(t)|\lambda_j) \tag{3}$$

where $\mathcal{R}^i$ shows an integer indicating the proto symbol of the highest likelihood. Fig.5 shows the image of cluster analysis for compensating the sparseness of the proto symbols. The Gaussian of the proto symbol j of i is then obtained as follows:

$$\boldsymbol{\mu}_{\mathcal{PS}_j^i} = \frac{1}{n_j^i}\mathrm{SUM}\{\boldsymbol{x}^i(t)|\mathcal{R}^i(t) = j\} \tag{4}$$

$$\boldsymbol{\Sigma}_{\mathcal{PS}_j^i} = \frac{1}{n_j^i}\mathrm{SUM}\{(\boldsymbol{x}^i(t) - \boldsymbol{\mu}_{\mathcal{PS}_j^i})(\boldsymbol{x}^i(t) - \boldsymbol{\mu}_{\mathcal{PS}_j^i})^T|\mathcal{R}^i(t) = j\} \tag{5}$$

where n_j^i denotes the number of observations that are recognized as associated with proto symbol j.

3.4 Motion Generation

Using the Gaussian computed in the previous subsection, we can generate a motion pattern of the robot indicated by point $\boldsymbol{x}^H(t)$ in the proto symbol space as follows:

$$\boldsymbol{o}_G(t) = \sum_{k=1}^{N_{\mathcal{PS}}{}^H} w_k \boldsymbol{o}_{Gk}(t) \tag{6}$$

$$w_j(t) = \frac{P(\boldsymbol{x}^H(t)|\lambda_j^H)}{\sum_{k=1}^{N_{\mathcal{PS}}{}^H} P(\boldsymbol{x}^H(t)|\lambda_k)} \tag{7}$$

where $P(\boldsymbol{x}^H(t)|\lambda_j^H)$ is the likelihood of a point $\boldsymbol{x}^H(t)$ with respect to the j-th proto symbol. $\boldsymbol{o}_{Gk}(t)$ means a generated motion pattern by the k-th proto symbol.

In order to use the generated motion patterns for the motion of humanoid robot, we will have to consider dynamical consistency, discontinuity at switching motion patterns, and the other constraints such as work space of joints and self-collision and appropriately modify them in realtime.

4 Experiments

The experiments of mimetic communication theory were conducted. Small-size humanoid robot, UT-*mu* magnum [18] was used. The realtime motion capture system was used to measure the whole body motion of a human and their interaction was investigated. The proto symbols and the proto symbol space were developed to model the motion patterns of the humanoid robot. The same proto symbol space was used for recognition of the human subject.

The meta proto symbol space was developed by showing the typical fighting scenes of two human subjects. The fights of the humanoid robot and the human subject were demonstrated at AICHI EXPO2005 in June 2006. They did not make physical contacts, rather they fought only in the virtual screen.

The sampling time for the motion capture is 30ms. We used the model of a humanoid robot [20] with 4 active joints in each arm, 6 active joints in each leg. The motion patterns are therefore represented by sequences of 46 dimensional vectors. The window span of motion data for the recognition is 180ms, which means that the motion data includes only 6 frames of captured data.

The output motion patterns of humanoid robots were modified in realtime to consider dynamical consistency, discontinuity at switching motion patterns, and the other constraints.

The stage at the EXPO is shown in Fig.**??**. The overall experimental system was set up as shown in Fig.**??**.

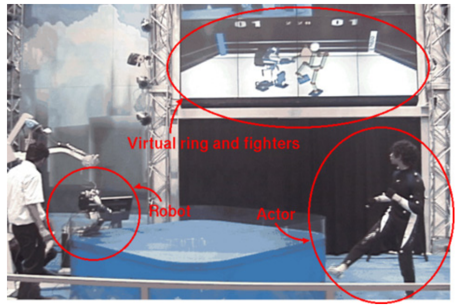

Fig. 6. Realtime virtual fight between a humanoid robot and a human subject at EXPO2005.

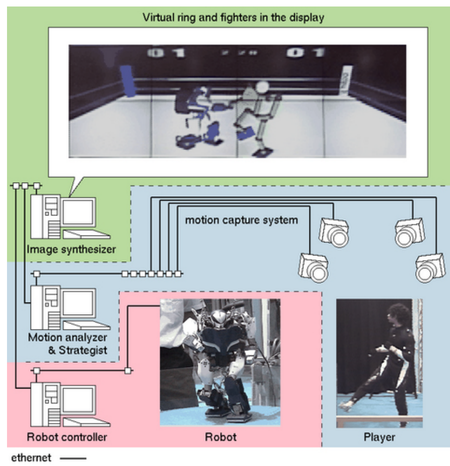

Fig. 7. Overall experimental setup for realtime virtual fight.

Fig.6 shows the virtual fighting scene between the humanoid robot and the human subject. In this figure, we see that the robot bends down against the human's punch and takes a punch at the human, and that the robot tries to protect with a leg against the human's kick and then give a kick to the human. The robot was capable of recognizing the human's behaviors and generating the suitable behaviors corresponding to the situation. These experimental results, we claim that the mimetic communication model is valid for acquiring primitive communication ability.

5 Conclusion

The mimesis model bridges the continuous motion patterns of the body of robot and the system of symbols. In this paper, we developed a fundamen-

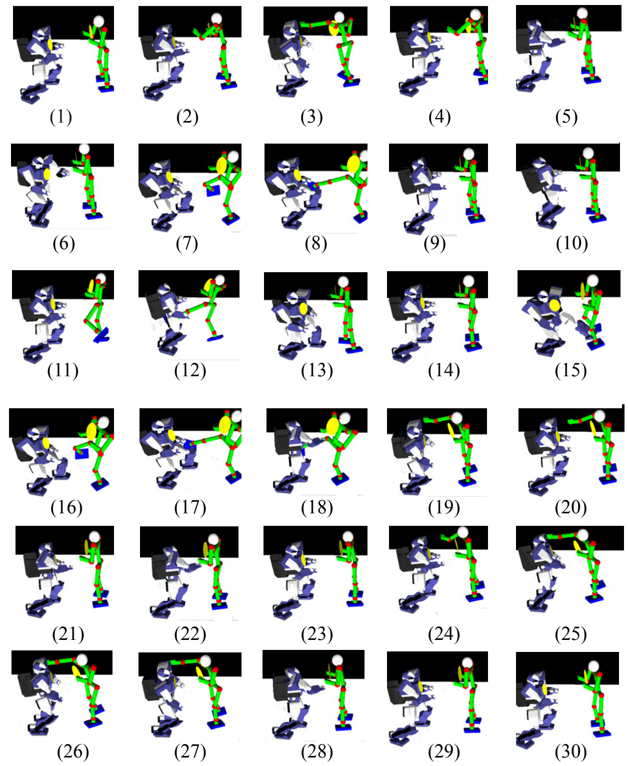

Fig. 8. Experimental result of interaction between the robot and the human.

tal theory to enable behavioral interactions between humanoid robots and humans. The interaction is supported by mimetic communication.

A hypothesis for designing fundamental interaction, namely naturally drifting interaction was established. It was to short-circuit the recognition output and the generation input of the meta proto symbol space. Because the naturally drifting interaction can be modeled to estimate the states of interaction and attempt to maintain the flow of states.

The mimetic communication theory was integrated into the realtime fighting demonstration of a humanoid robot and a human subject in the virtual screen. The experimental results showed the effectiveness of the theory.

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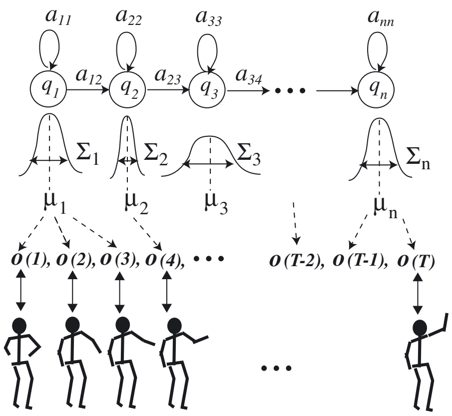

Fig. 9. A continuous Hidden Markov Model with left-to-right type state transition and continuous output vectors.

num. The experiments were conducted for the demonstration at EXPO2005, Nagoya, Japan as a part of NEDO Prototype Robot Project.

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Appendix

Mimesis Model [9]

The mimesis model consists of a set of proto-symbols that allow bidirectional computation of recognition and generation of the whole-body motions, just like the mirror system. A set of the stochastic parameters of a Hidden Markov Model (HMM) acquired for a segmented whole-body motion is considered a proto-symbol. In the literature [9], the pseudo-distance is defined between the proto-symbols, that allows to form an Euclidean space to interpolate and extrapolate the proto-symbols. The Euclidean space is named the proto-symbol space.

The left-to-right model for state transition and the continuous HMMs were adopted to construct the mimesis model as shown in Fig.9. A HMM is defined by a set of stochastic parameters $\lambda = \{\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\Pi}\}$, where $\boldsymbol{A} = \{a_{ij}\}$ is a matrix of state transition probability from node i to node j, $\boldsymbol{B} = \{b_i\}$ is a vector of output probability, and $\boldsymbol{\Pi} = \{\pi_1, \pi_2, \cdots, \pi_n\}$ is a set of initial node probability. The probability desity functions are assumed Gaussian as follows:

$$b_i(\boldsymbol{x}) = \frac{1}{\sqrt{(2\pi)^m |\boldsymbol{\Sigma}_i|}} \exp\{\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu}_i)^T \boldsymbol{\Sigma^{-1}}_i (\boldsymbol{x} - \boldsymbol{\mu}_i)\} \tag{8}$$

where $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ denote the mean vector and the covariance matrix of node i. $\boldsymbol{x}$ is an m-dimensional input vector. The parameters of HMM are computed by the Baum-Welch algorithm [19]. For computational efficiency the covariance matrix was approximated by a diagonal matrix with its diagonal elements.

Motion recognition is to find one among all the HMMs whose probability $P(\boldsymbol{O}|\lambda)$ to generate the observed motion pattern $\boldsymbol{O}$ is maximum.

Triple Averaging for Motion Generation

Motion generation is to recover the motion patterns encoded by the proto symbols. This paper proposes the triple averaging method for motion generation, which is explained as follows:

step1 Compute a sequence of state transition $\boldsymbol{Q}_G$ using the transition probability $\boldsymbol{A}$ and random variables.

step2 Repeat *step1* for n_q times and obtain $\boldsymbol{Q}_{G1}$, $\boldsymbol{Q}_{G2}, \cdots, \boldsymbol{Q}_{Gn_q}$. Compute the mean state transition $\bar{\boldsymbol{Q}}_G$ by simply averaging them.

$$\bar{\boldsymbol{Q}}_G = \{q_{s_k}\} \qquad s_k = \mathrm{int}(\frac{1}{N}\sum_i^N s_{k_i}) \tag{9}$$

where $\boldsymbol{Q}_{G_i} = \{q_{s_{k_i}}\}$. s_k represents the state number at time k. If the state at time k is q_j, then $s_k = j$ and $s_{k+1} = j$ or $j+1$. If $s_k = n$ or null, then $s_{k+1} =$ null.. N is the number of s_{k_i} that are not null.

step3 Compute a sequence of output vector $\hat{\boldsymbol{O}}_G$ according to the mean state transition nodes $\bar{\boldsymbol{Q}}_G$, using the output vector probability $\boldsymbol{B}$ and random variables.

step4 Repeat *step3* for n_o times and obtain output vector sequences $\hat{\boldsymbol{O}}_{G1}$, $\hat{\boldsymbol{O}}_{G2}, \cdots, \hat{\boldsymbol{O}}_{Gn_o}$. Taking their average, compute the mean output vector sequence $\bar{\boldsymbol{O}}_G$.

step5 Repeat *step1* through *step4* for n_t times and obtain the mean output vectors $\bar{\boldsymbol{O}}_{G1}$, $\bar{\boldsymbol{O}}_{G2}, \cdots, \bar{\boldsymbol{O}}_{Gn_t}$. Taking their average, finally compute the generated motion pattern $\boldsymbol{O}_G$.

Inamura's generation process [9] included double averaging of *step2* and *step4*. The third averaging in *step5* was effective to deliver a smooth output vector sequence even when the total cost of averaging was maintained constant.

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