JUMPS: Joints Upsampling Method for Pose Sequences

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Abstract—Human Pose Estimation is a low-level task useful for surveillance, human action recognition, and scene understanding at large. It also offers promising perspectives for the animation of synthetic characters. For all these applications, and especially the latter, estimating the positions of many joints is desirable for improved performance and realism. To this purpose, we propose a novel method called JUMPS for increasing the number of joints in 2D pose estimates and recovering occluded or missing joints. We believe this is the first attempt to address the issue. We build on a deep generative model that combines a GAN and an encoder. The GAN learns the distribution of high-resolution human pose sequences, the encoder maps the input low-resolution sequences to its latent space. Inpainting is obtained by computing the latent representation whose decoding by the GAN generator optimally matches the joints locations at the input. Post-processing a 2D pose sequence using our method provides a richer representation of the character motion. We show experimentally that the localization accuracy of the additional joints is on average on par with the original pose estimates.

I. INTRODUCTION

Human Pose Estimation (HPE) refers to the problem of predicting joints position (either in 2D or 3D) of a person in an image or video. It has been a topic of active research for several decades, and all state-of-the-art solutions rely on deep learning [1]–[5]. Even then, the best approaches extract skeletons with a limited number of joints, usually from 12 to 16, which is too rough for the movie industry or video games applications. This issue concerns both the 2D and 3D cases since 3D joint extraction almost always relies on 2D pose estimation. Moreover, these approaches still fail in the presence of strong foreshortening, left-right ambiguities, (self)-occlusions, or on previously unseen complex poses.

In this paper we improve on state-of-the-art HPE solutions by upsampling human joints and inpainting occluded ones, thereby paving the way for downstream applications that
require higher skeleton resolution. Starting with a temporal sequence of partially occluded poses, we recover missing joint locations and improve the resolution of the skeleton animation by estimating the positions of additional joints. To the best of our knowledge, no work has been previously proposed to recover missing joints or increase joints resolution of animated skeletons. We believe that enriching the representation helps in many cases, especially for extremities such as feet/toes and hands. A better extraction of the former provides a better visualisation and understanding of the motion. For instance, extracting the toe in addition to the ankle provides a better sense of feet contacts.

To this purpose, we draw inspiration from past research on human pose, motion modeling and image inpainting based on deep generative models: we leverage a deep generative network that provides an effective prior on spatio-temporal representation. The method relies on temporal sequence analysis since motion is key to recover missing joints. We propose a method to upsample and inpaint an animated skeleton to infer the locations of missing or unseen joints and provide a higher-resolution representation of the body pose. To this purpose we leverage a deep generative network that we train with moving skeleton sequences, rather than static poses, in order to better disambiguate the estimation of missing joint locations.

As illustrated in Fig. 2 our model consists of a GAN coupled with a variational autoencoder (VAE) that assumes a normal distribution in the latent space and stabilizes the training of the GAN. The upper right part (blue) is the basis of our model: a Generative Adversarial Network (GAN) with generator $G$ and discriminator $D$: the bottom left part (green) depicts how the encoder $E$ and the generator $G$ together yield an autoencoder (AE) scheme; $P_z$ and $P_{data}$ denote the prior and data distribution respectively.

In summary, our paper proposes the following contributions:

- a novel method based on deep generative modeling for inpainting 2D pose sequences and enriching the joints representation. The method relies on temporal sequence analysis since motion is key to recover missing joints.
- a hybrid GAN/autoencoder architecture; we show that the autoencoder is crucial for a better convergence and accuracy.
- We show that optimization in latent space is greatly improved by adding a Procrustes alignment at each iteration.
- We provide qualitative and quantitative assessments of the effectiveness of our method on the MPI-INF-3DHP human pose dataset.

II. RELATED WORK

**Human pose modeling:** Autoencoder architectures have been leveraged to learn models of human pose in the context of human pose estimation [6] and character animation synthesis and editing [7]. In [6] the latent space of the autoencoder encodes a structural prior on human pose. Mapping input images to this latent space provides guarantees as to the validity of the generated poses. Independently, [7] applies the same concept to temporal chunks of human poses, thereby capturing in the latent space a model of human motion. This model is mapped to semantic parameters for intuitive control by creative artists.

**Deep generative inpainting:** Deep generative models have demonstrated impressive performance on image inpainting [8]–[11]. For this task the need to faithfully reproduce the visible surroundings of missing image regions adds an additional constraint to the generative synthesis process and requires a mapping from the data space to the latent space of the generative model. Yeh et al. [9] compute the latent code from the corrupted image in the inference stage by backpropagating the gradients of a GAN generator network. In their seminal paper [12], Pathak et al. take a different approach that builds on the combination of a GAN and an autoencoder. The encoder provides the mapping from the input images to the latent space while the decoder acts as the generator network. [10] enriches this architecture with two discriminators to separately capture the small-scale and large-scale image texture, and [11] further adds a self-attention module to better take advantage of distant image patches to fill the missing regions. [8] replaces the autoencoder with a Variational Autoencoder (VAE) [13] and incorporates an image classifier to specialize the generative process to sub-categories. Our work leverages a deep network architecture combining a GAN and an autoencoder in the spirit of the latter approaches and adapts it to human pose data. We optimize our upsampling and inpainting process for temporal chunks of data and develop a generative model that captures both the static and dynamic aspects of human biomechanics.

III. METHOD

**A. Overview**

We propose a method to upsample and inpaint an animated skeleton to infer the locations of missing or unseen joints and provide a higher-resolution representation of the body pose. To this purpose we leverage a deep generative network that we train with moving skeleton sequences, rather than static poses, in order to better disambiguate the estimation of missing joint locations.
with an encoder, both forming an autoencoder where the generator plays the role of the decoder. It benefits from the generative power of GANs and mitigates instability during training by introducing supervision from the encoder.

B. Detailed Architecture

Our network conforms to the architecture of Deep Convolutional GANs (DCGANs) [19], using fractionally-strided transposed convolutions in the generator and strided convolutions in the discriminator (see Fig. 4). DCGANs also use Rectified Linear Units (ReLU) as activation functions in the generator and Leaky ReLU (LReLU) in the discriminator. Moreover, batch Normalization (BN) is also applied after almost each convolutional layer. Except for the output size of its final layer, the encoder has the same architecture as the discriminator.

C. Training

In this section we describe the representation used for joint position data, the loss functions and the optimization procedure.

Data Representation: A 2D pose sequence is usually represented as a 3-dimensional tensor containing the 2D coordinates of each joint at each frame. To obtain meaningful and efficient convolutions, we rearrange the joints as shown in Fig. 3. In this representation, each entry holds the 2D coordinates for two joints (i.e., four channels). Symmetric joints (e.g., feet, knees, etc.) are paired to form an entry, while joints in the axial skeleton (e.g., pelvis, thorax, etc.) are duplicated in order to obtain consistent four-channel entries. This reformatting of data to a rectangular 2D grid allows to use regular 2D convolutions in our deep network.

Notation: In the following, we note $E$, $G$ and $D$ the encoder, the generator and the discriminator networks, respectively. In addition $P_z$ and $P_{\text{data}}$ denote the latent and the data distributions respectively. Finally, $P_z$ stands for the distribution of uniformly sampled points along straight lines between pairs of points sampled from the data distribution $P_{\text{data}}$ and the generator distribution, i.e., $P_z$ mapped through $G$, as defined in [17].

Adversarial Loss: Traditionally, a GAN consists of a generator and a discriminator. The former is trained to produce realistic samples while the latter aims at distinguishing those from real samples, both competing against each other. The ability to generate realistic samples can be expressed more formally as the similarity between two probability distributions that are the data distribution and the distribution of samples produced by the generator. The original formulation of GANs [15] measures the similarity with the Jensen-Shannon divergence. However, this divergence fails to provide meaningful values when the overlap between the two distributions is not significant which often makes GANs quickly diverge during training. Arjovsky et al. [16] introduced Wasserstein GANs (WGANs), showing that, under the hypothesis that the discriminator is 1-Lipschitz, the Jensen-Shannon divergence can be replaced by the Wasserstein distance that have better properties for convergence. Then, Gulrajani et al. [17] propose a gradient penalty term in the WGAN loss function to enforce the 1-Lipschitz hypothesis on the discriminator. Therefore, we opt for the gradient-penalized WGAN and have the following loss functions for the generator and the discriminator, respectively:

$$L_G = \mathbb{E}_{z \sim P_z} \left[ -D(G(z)) \right]$$
$$L_D = \mathbb{E}_{z \sim P_z} \left[ D(G(z)) \right] - \mathbb{E}_{x \sim P_{\text{data}}} \left[ D(x) \right] + \lambda_{gp} \mathbb{E}_{\tilde{z} \sim P_z} \left[ \| \nabla_{\tilde{z}} D(\tilde{z}) \|_2^2 - 1 \right]^{-2}$$

where $\lambda_{gp}$ is the gradient penalty coefficient.

Reconstruction Losses: Like autoencoders, our model is encouraged to reconstruct inputs that are encoded and then decoded through a reconstruction loss minimizing differences between inputs and outputs. We also incite our model to be consistent when generating and then encoding from latent codes sampled from the prior distribution with a backward reconstruction loss, as in cycle-consistent VAEs [14]. Such backward reconstruction loss facilitates the convergence but more importantly enforces the distribution of the encoder outputs to match the prior distribution $P_z$ imposed on our GAN. As a result, the total loss in the autoencoding scheme
is

\[ \mathcal{L}_{AE} = \mathcal{L}_{Rec} + \mathcal{L}_{backward} \]  

(3)

Computational flows conducting to this loss are illustrated in Fig. 5b. \( \mathcal{L}_{Rec} \) itself made up of two terms penalizing respectively the joints position and velocity errors of the reconstructed sample \( \hat{x} = G(E(x)) \) with respect to the ground truth \( x \). More formally, we use the \textit{mean per joint position error} (MPJPE) [22] to quantify joint position errors:

\[ MPJPE(x, \hat{x}) = \frac{1}{J}\sum_{j=1}^{J} \|x_j - \hat{x}_j\|_2 \]  

(4)

where \( j \) and \( f \) denote the joint and frame considered; \( J \) and \( F \) are the numbers of joints and frames respectively.

In analogy to the MPJPE, we define the \textit{mean per joint velocity error} (MPJVE) as

\[ MPJVE(x, \hat{x}) = \frac{1}{J}\sum_{j=1}^{J} \left\| (v_j(x) - v_j(\hat{x})) \right\|_2 \]  

(5)

where \( v(\cdot) \) computes the velocity of each joint at each frame as the position difference between the current and previous frame. This secondary term penalizing velocity errors acts as a powerful regularizer that accelerates the convergence in early iterations and also reduces temporal jitter in the joint locations of the generated pose sequences. Hence, \( \mathcal{L}_{Rec} \) is the weighted sum of Eq. (4) and Eq. (5):

\[
\mathcal{L}_{Rec} = \frac{\lambda_p}{\sum_{z \sim \mathcal{P}_{data}} \mathcal{L}_{AE}} \mathcal{L}_{AE}(x, \hat{x}) + \frac{\lambda_s}{\sum_{z \sim \mathcal{P}_{data}} \mathcal{L}_{AE}} \mathcal{L}_{AE}(x, \hat{x})
\]  

(6)

where \( \lambda_p \) and \( \lambda_s \) are the weights. The second component \( \mathcal{L}_{backward} \) of our autoencoder’s objective focuses on the reconstruction of the latent code \( z \) sampled from the prior distribution \( \mathcal{P}_{z} \). It minimizes the Mean Squared Error (MSE) between \( z \) and its reconstructed version \( \hat{z} = E(G(z)) \):

\[
\mathcal{L}_{backward} = \frac{\lambda_z}{\sum_{z \sim \mathcal{P}_{z}} \mathcal{L}_{AE}} \mathcal{L}_{AE}(z, \hat{z})
\]  

(7)

Mixed Loss: We further encourage the generation of realistic sequences by adding a loss term to penalize unrealistic reconstructed pose sequences. Here we make use of the discriminator to tell both the generator and the encoder whether the reconstructed pose sequence \( \hat{x} = G(E(x)) \) is realistic or not. We use the same formulation as for the generator adversarial loss (see in Eq. 1) but applied to \( \hat{x} \) instead of \( G(z) \):

\[ \mathcal{L}_{Mix} = \lambda_m \mathbb{E}_{z \sim \mathcal{P}_{z}} [-D(\hat{x})] \]  

(8)

\textbf{Optimization:} In summary, the encoder, the generator and the discriminator are optimized w.r.t. the loss functions \( \mathcal{L}_{AE} + \mathcal{L}_{Mix} \), \( G \) + \( AE \) + \( L_{Mix} \) and \( D \), respectively. Similarly to a GAN, during the training we optimize at each iteration the discriminator in a first step and then the generator and the encoder. Fig. 5 illustrates the computational flows through the network during both training steps.

\textbf{Spatio-Temporal Variance Regularization:} GANs are known to produce sharp samples, but for the considered task this can lead to perceptually disturbing temporal jitters in the output pose sequences. To optimize the tradeoff between sharpness and temporal consistency, we feed the discriminator with stacked joint positions and velocities (computed for each joint at each frame as the position difference between the current and previous frame). The velocities favour the rejection of generated samples that are either temporally too smooth or too sharp. This idea is conceptually inspired from [18], where the variation of generated samples is increased by concatenating minibatch standard deviations at some point of the discriminator.

\textbf{D. Inference}

We leverage the human motion model learnt by the generator to recover missing joints in an input pose sequence \( x \). Given \( x \), we optimize \( z \) using gradient backpropagation across the generator network of a contextual loss that minimizes the discrepancy between \( G(z) \) and \( x \) on available joints. To this contextual loss we add a prior term that maximizes the discriminator score on the generated pose sequence. This process is closely related to the semantic image inpainting approach in [9]; however we take advantage of our encoder to compute a starting latent code \( z = E(x) \) as in [8]. This approach also applies to upsampling, considering that the added joints are missing in the input.

Formally, we first solve

\[ z^* = \arg\min_z \mathcal{L}_{Inp}(x, z) \]  

(9)
by gradient descent where $L_{1lp}$ is our inpainting objective function composed of a contextual loss and a prior loss. Then, we generate $x^* = G(z^*)$ that best reconstructs $x$ w.r.t $L_{1lp}$.

**Inpainting Loss Function:** Our contextual loss minimizes the weighted sum of MPJPE and MPJVE between the input pose sequence $x$ and the generated pose sequence $\hat{x} = G(z)$. Additionally, the prior loss maximizes the discriminator score $D(\hat{x})$ on the generated pose sequence:

$$L_{1lp} = \gamma_p \text{MPJPE}(x, \hat{x}) + \gamma_s \text{MPJVE}(x, \hat{x}) + \lambda_d D(\hat{x})$$

**Post-Processing:** At each gradient descent step, we generate the pose sequence $\hat{x} = G(z)$. At this point, we additionally use the fact that we are given a pose sequence $x$ to be inpainted by optimally translating, scaling and rotating $\hat{x}$ to match $x$. This process (known as Ordinary Procrustes Analysis) has a low overhead but makes the gradient descent convergence several times faster and improves inpainting results.

**Pose Sequence Length:** Our deep network requires pose sequences to have a constant number of frames $F$. Here we describe a simple mechanism to handle longer variable-length pose sequences. Given a pose sequence $x$ longer than $F$ frames, the idea is to independently inpaint fixed-length subsequences of $x$ and then concatenate the results into a single inpainted pose sequence having the same length as $x$. Using this process there is no guarantee that two consecutive subsequences will be smoothly concatenated. To prevent such discontinuities in the generated sequences we use half overlapping subsequences. At each temporal sample where an overlap is present we select among the candidate inpainted frames the one closest to the input, in the sense of the minimal contextual loss term in $L_{1lp}$.

### IV. Experiments

#### A. Datasets and Metrics

**Training and test sets:** We rely on **MPI-INF-3DHP** [21] for our experiments. This dataset contains image sequences in which 8 actors perform various activities with different sets of clothing. This dataset is well suited for our task of joints upsampling since it is one of the public databases having the highest skeleton resolution, i.e. skeletons with 28 joints. Since our method focuses on fixed length 2D pose sequences, we generated a set of around 835K 2D pose sequences of 24 frames (i.e., $F=24$) each using projections of the original 3D pose data from randomized camera viewpoints. We also selected around 166K images annotated with 2D poses directly from **MPI-INF-3DHP** with no preprocessing for testing.

**Evaluation Metrics:** We report our experiments results with the Percentage of Correct Keypoints normalized with Head size (PCKh) [26] and the Area Under the Curve (AUC) [27]. PCKh metric considers a joint as correct if its distance to the ground truth normalized by head size is less than a fixed threshold and the AUC aggregates PCKh over an entire range of thresholds. We use the common notation PCKh@α to refer to PCKh with threshold α and we compute the AUC over the range $[0, 1]$ of thresholds.

#### B. Implementation Details

Our deep network (see Fig. 4 for detailed architecture) has about 3 millions learnable parameters almost equally distributed over the encoder (1’148’096), the generator (1’148’480) and the discriminator (1’115’393). Our implementation is in Python and deeply relies on PyTorch library. Training and experiments have been executed on a NVIDIA Tesla P100 PCIe 16GB.

**Training:** We trained our model for 60 epochs (about 11 hours) with a minibatch size of 256 using the Adam algorithm [20] with optimization hyperparameters $\alpha = 0.0001$, $\beta_1 = 0.5$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$. We followed the suggestions for DCGANs from [19] to reduce (w.r.t. [20] suggestions) $\alpha$ and $\beta_1$. As in [19], we observed that $\beta_1 = 0.5$ helped to stabilize the training.

We set the Wasserstein gradient penalty weight $\lambda_{gp}$ to 10 as proposed in [17], and our loss weights $\lambda_p, \lambda_s, \lambda_d$ and $\lambda_m$ to 200, 100, 2 and 1 respectively. We empirically found these values to work well.

**Inference:** We compute the latent code again using the Adam optimization algorithm with $\alpha = 1$, $\beta_1 = 0.8$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$. The weights of the inpainting loss are set to $\gamma_p = 10$, $\gamma_s = 5$ and $\gamma_d = 15$. We stop the optimization after 200 iterations. These hyperparameter values has been chosen to make the optimization in a limited number of iterations and avoid matching noise or imperfections in inputs.

### Table I

Results of the joint upsampling experiments. We upsample back to 28 joints a ground truth 2D pose sequence purposefully downsampling to 12 joints. Removing Procrustes alignment (w/o P.A.) and the encoder (w/o ENC.) substantially degrades performance. See the text for the definition of the performance metrics.

| method              | PCKh@0.1 | PCKh@0.5 | PCKh@1.0 | AUC     |
|---------------------|----------|----------|----------|---------|
| JUMPS w/o P.A.      | 0.0368   | 0.4384   | 0.6814   | 0.3912  |
| JUMPS w/o ENC.      | 0.1701   | 0.8259   | 0.9678   | 0.7005  |
| JUMPS w/o overlap   | 0.5821   | 0.9648   | 0.9962   | 0.8727  |
| JUMPS               | 0.6096   | 0.9674   | 0.9965   | 0.8803  |

### Table II

Results of the Alpha Pose post-processing experiments. We perform inpainting and upsampling to 28 joints of 2D pose estimates obtained by running Alpha Pose on video sequences. The ablation studies confirm the conclusions drawn from the joint upsampling experiments (see Table I).

| method         | PCKh@0.1 | PCKh@0.5 | PCKh@1.0 | AUC     |
|----------------|----------|----------|----------|---------|
| AlphaPose      | 0.0941   | 0.7659   | 0.9157   | 0.6310  |
| JUMPS w/o P.A. | 0.0207   | 0.3423   | 0.6304   | 0.3249  |
| JUMPS w/o ENC. | 0.0537   | 0.6801   | 0.9059   | 0.5692  |
| JUMPS w/o overlap | 0.0831  | 0.7704   | 0.9277   | 0.6326  |
| JUMPS          | 0.0842   | 0.7723   | 0.9276   | 0.6341  |
To improve inference results we perform several optimizations of
the latent code in parallel for a single input, starting
from different initializations. One of these starting points is
computed as the output of the encoder fed by the input pose
sequence, the others are randomly sampled from the prior
distribution. We keep the one closest to the input, in the sense
of the inpainting loss $L_{inp}$.

C. Joints Upsampling

Our first experiment focuses on the upsampling task. We
downsample ground truth 28-joint pose sequences to 12 joints
that are common to the MPI-INF-3DHP dataset and AlphaPose
skeletons (see fig. 7 left), upsample them back to 28 joints
using our method, and compare the result to the original
sequence. Table I provides PCKh and AUC values for this
experiment. Assuming a typical human head size, the posi-
tioning error is less than 2.25 cm for half of the upsampled
joints (PCKh threshold = 0.1) and less than 11.25 cm for 95% of
them (PCKh threshold = 0.5).

D. 2D Human Pose Estimation

Our second experiment deals with the concrete use case of
inpainting and upsampling joints on a pose sequence obtained
using 2D Human Pose Estimation. We rely on AlphaPose
2 to preprocess videos in our test set. AlphaPose provides 12-
joint pose estimates that we post-process using our method
to recover missing (e.g., occluded) joints and upsample to 28
joints. Table II summarizes the results for this experiment. The
positioning accuracy is roughly the same for the inpainted /
upsampled joints and for the joints obtained by Human Pose
Estimation. Thus, our method enriches the pose information
without sacrificing accuracy. Fig. 7 illustrates how our method
is able to correct the right wrist position mispredicted by
AlphaPose based on the temporal consistency of the right
forearm movement.

2Implementation based on [23]–[25] available at https://github.com/MVIG-
SJTU/AlphaPose

E. Ablation Studies

1) Procrustes Analysis: line JUMPS w/o P.A. in tables I and II gives the joint positioning accuracy when the Procrustes
Analysis post-processing of our method (see section III-D) is
removed. Instead we map all pose sequences to the image
frame using the same affine transform. Rigidly aligning the
generated poses during the gradient descent optimization of
the latent code is critical to the performance of our approach.

2) Encoder: as shown by the accuracy estimates in lines
JUMPS w/o ENC. of the same tables, removing the encoder
in front of the GAN in our architecture, during both training
and inference stages, substantially degrades performance. The
encoder regularizes the generative process and improves the
initialization of the latent code at inference time, yielding
poses that better match the available part of the input skeleton.

3) Overlapping subsequences: Processing input sequences
with an overlap yields only a slight improvement of per-
formance over no overlap, the gain being stronger at high
accuracy levels. Indeed, since the optimization of the latent
code in our method matches the upsampled pose to the input,
an additional selection of the result closest to the input among
the several candidate poses at each frame when using an
overlap brings little gain in accuracy.

However, as illustrated on Fig. 6 we found that pro-
cessing overlapping chunks of frames noticeably improves
the temporal consistency of the output pose sequence. We
observed that the per-frame joint positioning accuracy drops
at the extremities of the processed chunks, probably because
of the reduced temporal context information there. Without
overlap this introduces an increased temporal jitter at the
chunk boundaries of the generated pose sequence, which is
likely to incur perceptually disturbing artifacts when applying
our method to, e.g., character animation.

V. CONCLUSION

In this paper we presented a novel method for human
pose inpainting focused on joints upsampling. Our approach
relies on a hybrid adversarial generative model to improve
the resolution of the skeletons (i.e., the number of joints)
with no loss of accuracy. To the best of our knowledge, this
is the first attempt to solve this problem with a machine learning technique. We have also shown its applicability and effectiveness to Human Pose Estimation. Our framework considers a 12-joint 2D pose sequence as input and produces a valuable 28-joint 2D pose sequence by inpainting the input. The proposed model consists of the fusion of a deep convolutional generative adversarial network and an autoencoder. Ablation studies have shown the strong benefit of the autoencoder, since it provides some supervision that greatly helps the convergence and accuracy of the combined model. Given an input sequence, inpainting is performed by optimizing the latent representation that best reconstructs the low-resolution input. The encoder provides the initialization and a prior loss based on the discriminator is used to improve the plausibility of the generated output. The obtained results are encouraging and open up future research opportunities. Better consistency of the inpainted pose sequences with true human motion could be obtained either by explicitly enforcing biomechanical constraints, or by extending the method to 3D joints, in order to benefit from richer positional information on the joints. Additionally, a potentially fruitful line of research would be to tackle as a whole, from a monocular image input, the extraction of 3D human pose and the upsampling of skeleton joints. Finally, we plan to study more genuine temporal analysis by using a different network architecture handling either longer or variable-length pose sequences (e.g., based on recurrent neural networks or fully convolutional networks).

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