

# PoseFix: Correcting 3D Human Poses with Natural Language

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## Abstract

Automatically producing instructions to modify one’s posture could open the door to endless applications, such as personalized coaching and in-home physical therapy. Tackling the reverse problem (i.e., refining a 3D pose based on some natural language feedback) could help for assisted 3D character animation or robot teaching, for instance. Although a few recent works explore the connections between natural language and 3D human pose, none focus on describing 3D body pose differences. In this paper, we tackle the problem of correcting 3D human poses with natural language. To this end, we introduce the PoseFix dataset, which consists of several thousand paired 3D poses and their corresponding text feedback, that describe how the source pose needs to be modified to obtain the target pose. We demonstrate the potential of this dataset on two tasks: (1) text-based pose editing, that aims at generating corrected 3D body poses given a query pose and a text modifier; and (2) correctional text generation, where instructions are generated based on the differences between two body poses. The dataset and the code are available at <https://europe.naverlabs.com/research/computer-vision/posefix/>.

## 1. Introduction

How many puzzles could you solve with two human body poses and a description of their differences? Call this description a feedback. It could be automatically generated by a fitness application based on the comparison between the gold standard fitness pose and the pose of John Doe, exercising in front of their smartphone camera in their living room (“straighten your back”). In another context, the feedback can be considered a modifying instruction, provided by a digital animation artist to automatically modify the pose of a character, without having to redesign everything by hand. This feedback could be some kind of con-

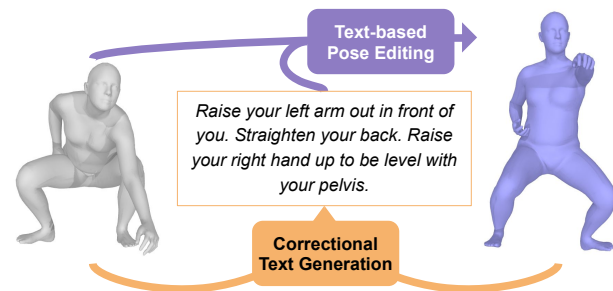


Figure 1: **Illustration of the tasks addressed with the new PoseFix dataset**, which consists of textual descriptions of the difference between two 3D body poses.

straint, to be applied to a whole sequence of poses (make them run, but “with hands on the hips!”). It could also be a hint, to guide pose estimation from images in failure cases: start from an initial 3D body pose fit, and give step-by-step instructions for the model to improve its pose estimation (“the left elbow should be bent to the back”).

In this paper, we focus on free-form feedback describing the change between two static 3D human poses (which can be extracted from actual pose sequences). Why so static? There exist many settings that require the semantic understanding of fine-grained changes of static body poses. For instance, yoga poses are extremely challenging and specific (with a lot of subtle variations), and they are static. Some sport motions require almost-perfect postures at every moment: for better efficiency, to avoid any pain or injury, or just for better rendering *e.g.* in classical dance, yoga, karate, *etc.* What is more, the realization of complex motions sometimes calls for precise step-to-step instructions, in order to assimilate the gesture or to perform it correctly.

Natural language can help in all these scenarios, in that it is highly semantic and unconstrained, in addition of being a very intuitive way to convey ideas. While 3D poses can be manually edited within a design framework [38], language is particularly efficient for non-experts or when direct manipulation is not possible. The pose semantic we propose

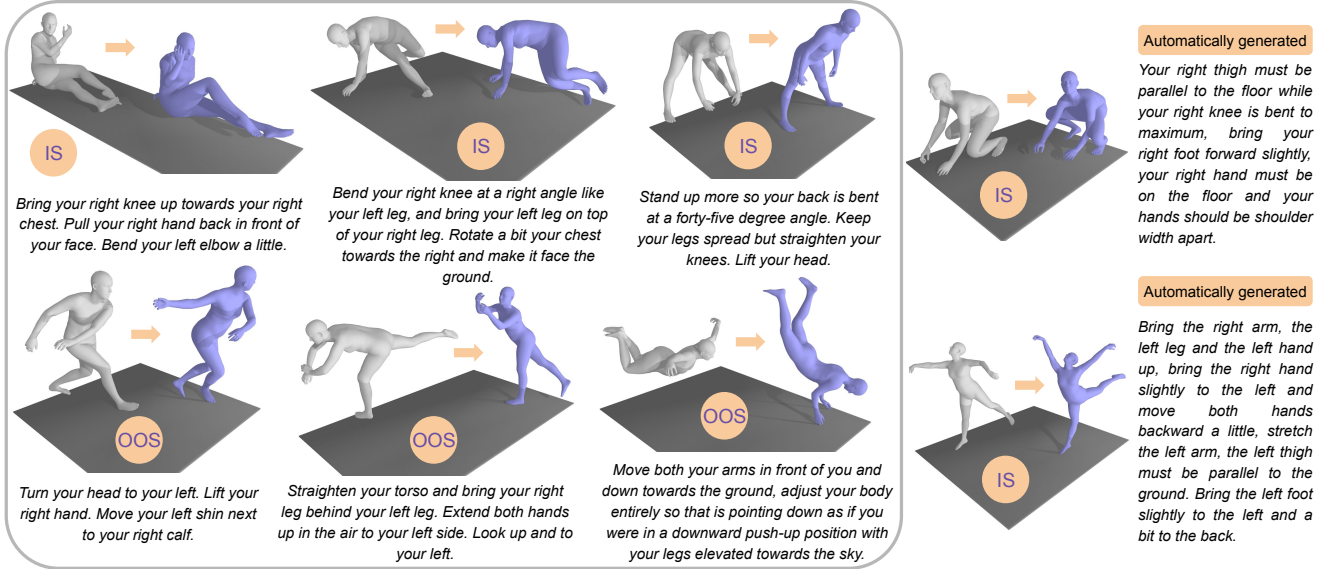


Figure 2: **Examples of pose pairs and their annotated modifier in PoseFix.** The source pose is shown in gray and the target pose in purple. Poses from in-sequence (*IS*) pairs are from the same Pose motion clip; unlike out-of-sequence (*OOS*) pairs.

to learn here can be leveraged for other modalities (*e.g.* images) or in other settings (*e.g.* robot teaching).

While the link between language and images has been extensively studied in tasks like image captioning [32, 21] or image editing [64], the research on leveraging natural language for 3D human modeling is still in its infancy. A few works use textual descriptions to generate motion [18, 54], to describe the difference in poses from synthetic 2D renderings [25] or to describe a single static pose [12]. Nevertheless, there currently exists no dataset that associates pairs of 3D poses with textual instructions to move from one source pose to one target pose. In this work, we thus introduce the PoseFix dataset, which contains over 6,000 textual *modifiers* written by human annotators for this scenario. In addition, we design a pipeline similar to [12], to generate modifiers automatically and increase the size of the data, see Figure 2 for some examples.

Leveraging the PoseFix dataset, we tackle two tasks: *text-based pose editing*, where the goal is to generate new poses from an initial pose and modification instructions, and *correctional text generation* where the objective is to produce a textual description of the difference between a pair of poses (see Figure 1). For the first task, we use a baseline consisting in a conditional Variational Auto-Encoder (cVAE). For the second, we consider a baseline built from an auto-regressive transformer model. We provide a detailed evaluation of both baselines, and show promising results.

In summary, our contributions are threefold:

- We introduce the PoseFix dataset (Section 3) that associates pairs of 3D human poses and human-written textual descriptions of their differences.

- We introduce the task of text-based pose editing (Section 4), that can be tackled with a cVAE baseline.
- We study the task of correctional text generation with a conditioned auto-regressive model (Section 5).

## 2. Related Work

**3D pose and text datasets.** AMASS [36] gathers several datasets of 3D human motions in SMPL [35] format. BABEL [47] and HumanML3D [18] build on top of it to provide free-form text descriptions of the sequences, similarly to the earlier and smaller Kit Motion-Language dataset [46]. These datasets focus on sequence semantic (high-level actions) rather than individual pose semantic (fine-grained egocentric relations). To complement, PoseScript [12] links static 3D human poses with descriptions in natural language about fine-grained pose aspects. However, PoseScript does not make it possible to relate two poses together in a straightforward way, as we attempt by introducing the new PoseFix dataset. In contrast to FixMyPose [25], the PoseFix dataset we introduce comprehends poses from more diverse sequences and the textual annotations were collected based on actual 3D data and not synthetic 2D image renderings (reduced depth ambiguity).

**3D human pose generation.** Previous works have mainly focused on the generation of pose sequences, conditioning on music [28, 29], context [10], past poses [61, 62], text labels [20, 44] and mostly on text descriptions [30, 1, 59, 2, 17, 45, 18, 54, 19, 26]. Some works push it one step further and also attempt to synthesize the mesh appearance [23, 60], leveraging large pretrained models like CLIP [48]. Similarly to PoseScript [12], we depart from generic actions and

focus on static poses and fine-grained aspects of the human body, to learn about precise egocentric relations. However, we consider two poses instead of one to comprehend detailed pose modifications. Different from ProtoRes [38], which proposes to manually design a human pose inside a 3D environment based on sparse constraints, we use text for controllability. As PoseScript and VPoser [42], an (unconditioned) pose prior, we use a VAE-based [27] model to generate the 3D human poses.

**Pose correctional feedback generation.** Recent advances in text generation have led to a shift from recurrent neural networks [53] to large pretrained transformer models, such as GPT [8]. These models can be effectively conditioned using prompting [39] or cross-attention mechanisms [49]. While multi-modal text generation tasks, such as image captioning, have been extensively studied [32, 21, 56] no previous work has focused on using 3D human poses to generate free-form feedback. In this regard, AIFit [15] extracts 3D data to compare the video performance of a trainee against a coach’s and provides feedback based on predefined templates. [63] also outputs predefined texts for a small set of exercises and [33] does not provide any natural language instructions, either. Besides, FixMyPose [25] is based on highly-synthetic 2D images.

**Compositional learning** consists in using a query made of multiple distinct elements, which can be of different modalities, as for visual question answering [4] or composed image retrieval [57]. Similarly to the latter, we are interested in bi-modal queries composed of a textual “modifier” which specifies changes to apply on the first element. Modifiers first took the form of single-word attributes [41, 37, 14] and evolved into free-form texts [58, 34]. While a large body of works focus on text-conditioned image editing [24, 7, 22] or text-enhanced image search [57, 5, 11], few study 3D human body poses. ClipFace [3] proposes to edit 3D morphable face models and StyleGAN-Human [16] generates 2D images of human bodies in very model-like poses. PoseTutor [13] provides an approach to highlight joints with incorrect angles on 2D yoga/pilate/kung-fu images. More related to our work, FixMyPose [25] performs composed image retrieval. Conversely to them, we propose to *generate* a 3D pose based on an initial static pose and a modifier expressed in natural language.

### 3. The PoseFix dataset

To tackle the two pose correctional tasks considered in this paper, we introduce the new PoseFix dataset. It consists of 135k triplets of  $\{pose\ A, pose\ B, text\ modifier\}$ , where pose  $B$  (the target pose) is the result of the correction of pose  $A$  (the source pose), as specified by the *text modifier*. The 3D human body poses were sampled from AMASS [36]. All pairs were captioned in Natural Lan-

guage thanks to our automatic comparative pipeline; 6157 pairs were additionally presented to human annotators on the crowd-source annotation platform Amazon Mechanical Turk. We next present the pair selection method, the annotations process and some dataset statistics.

#### 3.1. Pair selection process

**In- and Out-of-sequence pairs.** Pose pairs can be of two types: “*in-sequence*” (IS) or “*out-of-sequence*” (OOS). In the first case, the two poses belong to the same AMASS sequence and are temporally ordered (pose  $A$  happens before pose  $B$ ). We select them with a maximum time difference of 0.5 second, to have both textual modifiers describing precisely atomic motion sub-sequences and ground-truth motion. For an increased time difference between the two poses, they could be an infinity of plausible in-between motions, which would weaken such supervision signal. Out-of-sequence pairs are made of two poses from different sequences; to help generalize to less common motions and to study poses of similar configuration but different style, empowering “pose correction” beside “motion continuation”.

**Selecting pose B.** As we aim to obtain pose  $B$  from pose  $A$ , we consider that pose  $B$  is guiding the most the annotation: while the text modifier should account for pose  $A$  and refer to it, its true target is pose  $B$ . Thus, to build the triplets, we first choose the set of poses  $B$ . So to maximize the diversity of poses, we follow [12], and get a set  $S$  of 100k poses sampled with a farthest-point algorithm. Poses  $B$  are then iteratively selected from  $S$ .

**Selecting pose A.** The paired poses should satisfy two main constraints. First, poses  $A$  and  $B$  should be similar enough for the text *modifier* not to become a complete *description* of pose  $B$ : if  $A$  and  $B$  are too different, it is easier for the annotator to just ignore  $A$  and directly characterize  $B$  [58, 34]. Yet, we aim at learning fine-grained and subtle differences between two poses. Hence, we rank all poses in  $S$  with regard to each pose  $B$  based on the cosine similarity of their PoseScript semantic pose features [12]. Pose  $A$  is to be selected within the top 100. Second, the two poses should be different enough, so that the modifier does not collapse to oversimple instructions like ‘*raise your right hand*’, which would not compare to realistic scenarios. While we expect the poses to be quite different as they belong to  $S$ , we go one step further and leverage posecode information [12] to ensure that the two poses have at least 15 (resp. 20) low-level different properties for IS (resp. OOS) pairs.

**One- and Two-way pairs.** We consider all possible IS pairs  $A \rightarrow B$ , with  $A$  and  $B$  in  $S$ , that meet the selection constraints. Then, following the order defined by  $S$ , we sample OOS pairs: for each selected pair  $A \rightarrow B$ , if  $A$  was not already used for another pair, we also consider  $B \rightarrow A$ . We call such pairs ‘*two-way*’ pairs, as opposed to ‘*one-way*’ pairs. Two-way pairs could be used for cycle consistency.





which vary depending on the context (pose  $A$ ).

A few other annotation behaviors were found to be quite difficult to quantify, in particular “missing” instructions. Sometimes, details are omitted in the text because the context given by pose  $A$  is “taken for granted”. For instance, in the 3rd example shown in Figure 2, the “45-degree angle” is to be understood with regard to the “0 degree” plan defined by the back of the body in pose  $A$ . Moreover, the annotator did not specify how the position of the arms have changed, supposedly because this change comes naturally once the back is straighten up, from the structure of the kinematic chain. These challenges are inherent to the task.

Detailed statistics are presented in Tables 2 and 3.

#### 4. Application to Text-based Pose Editing

We introduce a VAE [27] baseline to perform text-based 3D human pose editing. Specifically, we aim to generate plausible new poses based on two input elements: an initial pose  $A$  providing some context (a starting point for modifications), and a textual modifier which specifies the changes to be made. Figure 4 gives an overview of our model.

**Data processing.** Poses are characterized by their SMPL-H [50] body joint rotations in axis-angle representation. Their global orientation is first normalized along the y-axis. For in-sequence pairs, the same normalization that was applied to pose  $A$  is applied to pose  $B$  in order to preserve information about the change of global orientation.

**Training phase.** During training, the model encodes both the query pose  $A$  and the ground-truth target pose  $B$  using a shared pose encoder, yielding respectively features  $\mathbf{a}$  and  $\mathbf{b}$  in  $\mathbb{R}^d$ . The tokenized text modifier is fed into a pre-trained embedding module to extract expressive word encodings. These are further processed by a learned textual model, to yield a global textual representation  $\mathbf{m} \in \mathbb{R}^n$ . Next, the two input embeddings  $\mathbf{a}$  and  $\mathbf{m}$  are provided to a fusing module which outputs a single vector  $\mathbf{p} \in \mathbb{R}^d$ . Both  $\mathbf{b}$  and  $\mathbf{p}$  then go through specific fully connected layers to produce the parameters of two Gaussian distributions: the posterior  $\mathcal{N}_b = \mathcal{N}(\cdot | \boldsymbol{\mu}(\mathbf{b}), \boldsymbol{\Sigma}(\mathbf{b}))$  and the prior  $\mathcal{N}_p = \mathcal{N}(\cdot | \boldsymbol{\mu}(\mathbf{p}), \boldsymbol{\Sigma}(\mathbf{p}))$  conditioned on  $\mathbf{p}$  from the fusion of  $\mathbf{a}$  and  $\mathbf{m}$ . Eventually, a sampled latent variable  $\mathbf{z}_b \sim \mathcal{N}_b$  is decoded into a reconstructed pose  $\hat{B}$ .

The loss consists in the sum of a reconstruction term  $\mathcal{L}_R(B, \hat{B})$  and the Kullback-Leibler (KL) divergence between  $\mathcal{N}_b$  and  $\mathcal{N}_p$ . The former enables the generation of plausible poses, while the latter acts as a regularization term to align the two spaces. The combined loss is then:

$$\mathcal{L}_{\text{pose editing}} = \mathcal{L}_R(B, \hat{B}) + \mathcal{L}_{KL}(\mathcal{N}_b, \mathcal{N}_p). \quad (1)$$

We use the same negative log likelihood-based reconstruction loss as in [12]: it is applied to the output joint rotations in the continuous 6D representation [65], and both

the joint and vertices positions inferred from the output by the SMPL-H [50] model.

**Inference phase.** The input pose  $A$  and the text modifier are processed as in the training phase. However, this time we sample  $\mathbf{z}_p \sim \mathcal{N}_p$  to obtain the generated pose  $\hat{B}$ .

**Evaluation metrics.** We report the Evidence Lower Bound (ELBO) for the size-normalized rotations, joints and vertices, as well as the Fréchet inception distance (FID) which compares the distribution of the generated poses with the one of the expected poses, based on their semantic PoseScript features. The ELBO and the FID are mostly sensitive to complementary traits (sample quality and support coverage respectively). When some settings do not improve all metrics; we then base our decisions on the metrics with the highest differential. While the ELBO is better suited to evaluate generative models than reconstruction metrics, for intuitiveness, we also report the the MPJE (mean-per-joint error, in mm), the MPVE (mean-per-vertex error, in mm) and the geodesic distance for joint rotations (in degrees) between the target and the best (*i.e.*, closest) generated sample out of  $N=30$  in all experiments.

**Architecture details and ablations.** We use the VPoser [42] architecture for the pose auto-encoder, resulting in features of dimension  $d = 32$ . The variance of the decoder is considered a learned constant [51]. We experiment with two different text encoders (Table 4, top): (i) a bi-GRU [9] mounted on top of pretrained GloVe word embeddings [43], or (ii) a transformer followed by average-pooling, processing frozen DistilBERT [52] word embeddings. We find that the transformer pipeline outperforms the other in terms of ELBO (+0.24 in average) when no additional pretraining is involved, supposedly because it uses already strong general-pretrained weights. Pretraining on our automatic modifiers brings the bi-GRU pipeline on par with the transformer one (+0.04). For simplicity, we will thereafter resort to the former.

For fusion, we use TIRG [57], a well-spread module for compositional learning. It consists in a gating mechanism composed of two 2-layer Multi-Layer Perceptrons (MLP)  $f$  and  $g$  balanced by learned scalars  $w_f$  and  $w_g$  such that:

$$\mathbf{p} = w_f f([\mathbf{a}, \mathbf{m}]) \odot \mathbf{a} + w_g g([\mathbf{a}, \mathbf{m}]). \quad (2)$$

It is designed to ‘preserve’ the main modality feature  $\mathbf{a}$  while applying the modification as a residual connection.

**Training data and augmentations ablations.** We experiment with several kinds of data augmentations and training data. Corresponding results are reported in Table 4 (bottom). First, we try left/right flipping by swapping the rotations of the left and right body joints (*e.g.* the left hand becomes the right hand) and changing the text accordingly. This improves the quality of the samples significantly (ELBO), especially when the model did not benefit

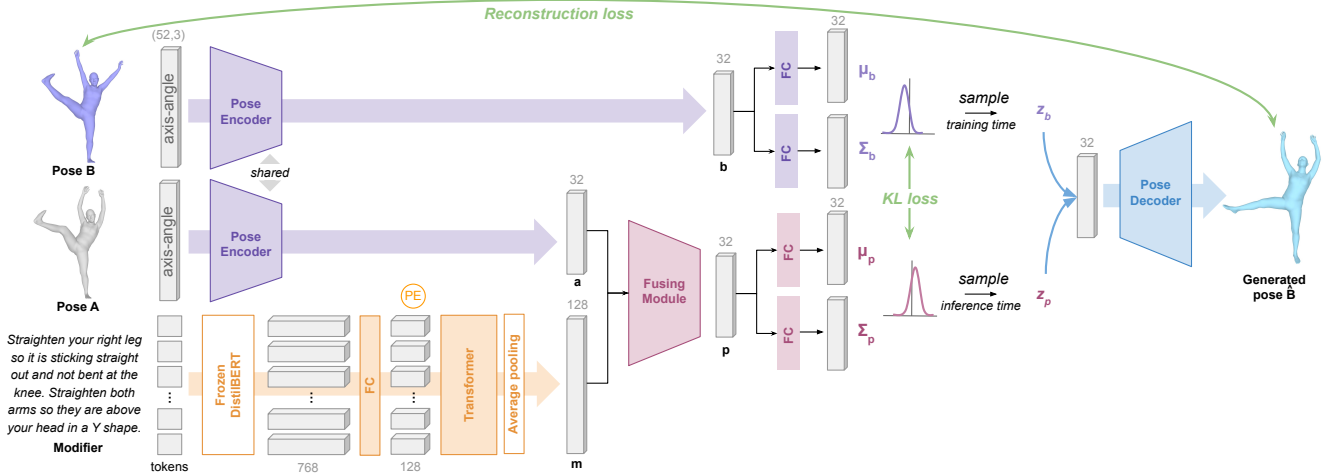


Figure 4: **Overview of our text-based pose editing baseline.** The top part represents a standard VAE, where poses are encoded into a Gaussian distribution. At training time, a latent variable is sampled and decoded into a pose to learn pose reconstruction. The bottom left part represents the conditioning: the text is encoded using a frozen DistilBERT with a small transformer on top. It is combined with source pose features in the *fusion module*, from which we predict a Gaussian distribution. A KL loss ensures the alignment of the distributions from the standard VAE and the conditioning. At test time, we sample from the latter to predict the target pose.

		FID ↓	ELBO ↑			Reconstruction ↓ (best of 30)		
			jts	v2v	rot	MPJE	MPVE	Geodesic
<b>Text Encoder (with/without pretraining)</b>								
without	GloVe + bi-GRU	<b>0.28</b>	0.61	<b>1.51</b>	0.50	278	217	9.89
	DistilBERT+transformer	0.36	<b>0.95</b>	<b>1.51</b>	<b>0.63</b>	<b>226</b>	<b>180</b>	<b>9.22</b>
with	GloVe + bi-GRU	<b>0.14</b>	<b>1.40</b>	<b>1.88</b>	<b>0.99</b>	<b>199</b>	<b>165</b>	<b>8.59</b>
	DistilBERT+transformer	0.17	1.37	1.84	0.93	201	167	8.70
<b>Data augmentations (with/without pretraining, GloVe+bi-GRU config)</b>								
without	no augmentation	0.14	1.40	1.88	<b>0.99</b>	199	165	8.59
	+ L/R flip	<b>0.28</b>	<b>1.10</b>	<b>1.73</b>	<b>0.58</b>	250	196	9.57
	+ paraphrases	0.31	0.90	1.45	<b>0.58</b>	<b>233</b>	<b>186</b>	<b>9.44</b>
	+ PoseMix	0.33	0.63	1.12	<b>0.58</b>	254	202	9.61
	+ PoseMix & PoseCopy	<b>0.22</b>	<b>1.03</b>	1.50	<b>0.78</b>	<b>221</b>	<b>178</b>	<b>9.07</b>
with	no augmentation	0.14	1.40	1.88	<b>0.99</b>	199	165	8.59
	+ L/R flip	0.14	<b>1.47</b>	<b>1.94</b>	0.97	197	163	8.65
	+ paraphrases	<b>0.13</b>	1.43	1.90	0.97	198	164	<b>8.58</b>
	+ PoseMix	0.19	0.68	1.13	0.91	214	174	8.74
	+ PoseMix & PoseCopy	<b>0.12</b>	1.23	1.71	<b>0.98</b>	208	172	8.75
+ L/R flip & paraphrases	<b>0.13</b>	<b>1.44</b>	<b>1.92</b>	0.97	<b>196</b>	<b>162</b>	8.62	

Table 4: **Text-based pose editing results** for various architectures, data augmentations and training strategies. We show the best result in bold and underline the second best.

from pretraining on diverse synthetic data (+37% average improvement of the ELBO).

Next, we use InstructGPT [39] to obtain 2 paraphrases per annotation. This form of data augmentation was found helpful, particularly when training on a small amount of data, *i.e.*, without pretraining (+20%).

In order to encourage the model to fully leverage the textual cue, we define *PoseMix*, which gathers both the PoseScript [12] and the PoseFix datasets. When training with PoseScript data, which consist in pairs of poses and textual descriptions, we set pose *A* to 0. We notice a mitigated improvement, and even a drop in performance in the pretrained case. One possible reason for that is the difference in for-

mulation between PoseScript descriptions (“*The person is ... with their left hand...*”) and PoseFix modifiers (“*Move your left hand...*”). Another is that the model then learns to ignore *A*, which is nonetheless crucial in the PoseFix setting. To circumvent this last-mentioned issue, we improve the balance of the training data by introducing *PoseCopy*. This consists in providing the model with the same pose in the role of pose *A* and pose *B*, along with an empty modifier, assuming that a non-existent textual query will force the model to attend pose *A*. The *PoseMix* & *PoseCopy* setting yields a great improvement over all metrics for the non-pretrained case (+41%). This further shows that the formulation gap was not the main issue. As a side product, the fusing branch is now able to work as a pseudo auto-encoder, and to output a copy of the input pose when no modification instruction is provided.

Eventually, the pretraining has a more significant impact than using any kind of data augmentation (+84%). Besides, the data augmentations become much less effective in this setting (+1%). The model thus benefits better from pretraining on a large set of new pairs with synthetic instructions, than training on more human-written modifiers of the same pose pairs. We overall obtain our best model by combining pretraining, left/right flip and paraphrases (last row).

**Detailed analysis.** In Table 5, we evaluate our best pose editing model on several subsets of pairs and with different input types.

First, we notice higher ELBO performance on the out-of-sequence (OOS) pair set compared to the in-sequence (IS) set, suggesting that pairs in the latter are harder. This can

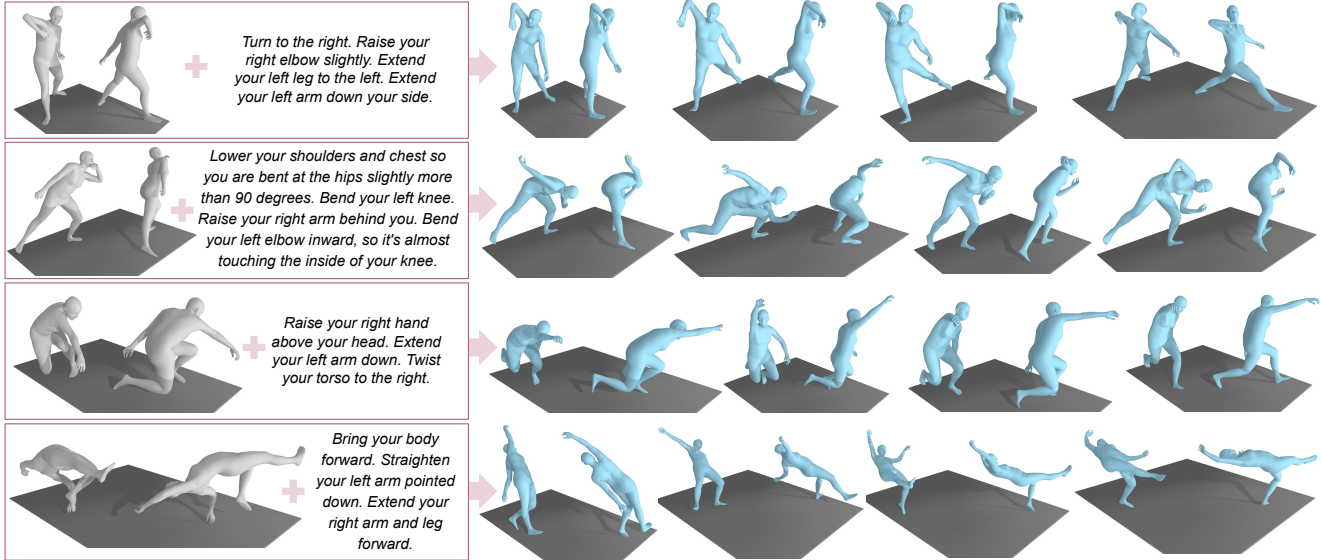


Figure 5: **Generated poses for the text-based pose editing task** on PoseFix queries from the left blocks. Two views of each pose are shown on the same ground plane for better visualization of the 3D. Generated poses are shown in blue. Original poses B from the PoseFix dataset are in the supplementary material.

	FID ↓		ELBO ↑			Reconstruction ↓ (best of 30)		
		jts	v2v	rot	MPJE	MPVE	Geodesic	
<b>Pair subset</b>								
in-sequence (530)	0.20	1.33	1.78	0.88	<b>188</b>	<b>154</b>	<b>8.47</b>	
out-of-sequence (709)	<b>0.11</b>	<b>1.53</b>	<b>2.02</b>	<b>1.04</b>	206	168	8.80	
full PoseFix test set (1239)	0.13	1.44	1.92	0.97	196	162	8.62	
<b>Input type (full PoseFix test set - 1239)</b>								
pose A only	0.17	1.43	<b>1.92</b>	<b>0.97</b>	219	180	8.91	
modifier only	1.05	1.30	<b>1.92</b>	0.92	378	339	13.03	
pose A + modifier	<b>0.13</b>	<b>1.44</b>	<b>1.92</b>	<b>0.97</b>	<b>196</b>	<b>162</b>	<b>8.62</b>	

Table 5: **Pose editing results for various subsets and input types**, using the best model as per Table 4.

be due to pose  $A$  and pose  $B$  being more similar in IS than OOS, as they belong to the same sequence with a maximum delay of 0.5s. We indeed measure a mean per joint distance of 311mm between  $A$  and  $B$  in IS vs. 350mm in OOS: the differences between IS poses thus ought to be more subtle, yielding more complex modifiers. This drop in ELBO performance shows also that the model struggles more with IS modifiers, meaning that it most probably generates, in average, poses that are close to pose  $A$ , – in other words, it would takes guesses in the surroundings of pose  $A$ . This would actually be a good fall-back strategy, because the two poses are rather similar in general. In the IS case, since pose  $A$  and pose  $B$  are particularly close to each other, the model may end up finding, with enough guesses, a pose closer to pose  $B$  than it would in the OOS case, where the two poses are more different. This could explain why the reconstruction metrics using the best sample out of 30 are lower for the IS subset than the OOS subset.

Next, we compare the results when querying with the *pose A only* or the *modifier only*. The former achieves already high performance, showing that the initial pose  $A$

alone provides a good approximation of the expected pose  $B$  – indeed, the pair selection process constrained pose  $A$  and pose  $B$  to be quite similar. The latter yields poor FID and reconstruction metrics: the textual cue is only a modifier, and the same instructions could apply to a large variety of poses. Looking around pose  $A$  remains a better strategy than sticking to the sole modifier in order to generate the expected pose. Eventually, both parts of the query are complementary: pose  $A$  serves as a strong contextual cue, and the modifier guides the search starting from it (the pose being provided through the gating mechanism in TIRG). Both are crucial to reach pose  $B$  (last row).

**Qualitative results.** Last, we present qualitative results for text-based 3D human pose editing in Figure 5. It appears that the model has a relatively good semantic comprehension of the different body parts and of the actions to modify their positions. Some egocentric relations (“*Raise your right elbow slightly.*”, first row) are better understood than others, in particular contact requirements (“*Bend your elbow so it’s almost touching the inside of your knee*”, second row). When missing some specifications, the model generates various pose configurations (*e.g.* the extent of the left leg extension in the first example). It can handle a number of instructions at once (third row), but may fail to attend all of them. Crouching and lying-down poses are the most challenging (see failure case in the last row, and how the crouch is hardly preserved in the third row).

## 5. Application to correctional text generation

We next present a baseline for correctional text generation. We aim to produce feedback in natural language ex-

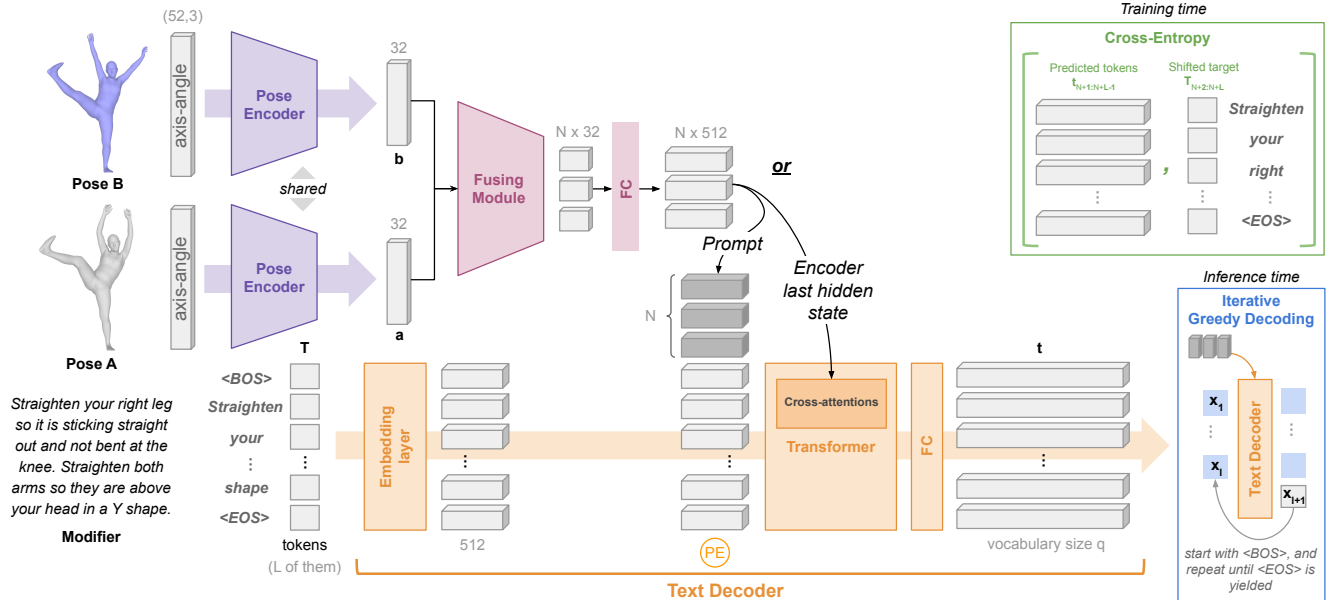


Figure 6: **Overview of our baseline for correctional text generation.** The bottom part represents a standard auto-regressive transformer model: the next word is predicted from the previously generated tokens. The decoder outputs a distribution of probabilities over the vocabulary for each token. The top part represents the conditioning on the pose pair: the two pose embeddings are fused together into a set of “pose tokens”, further used for conditioning via prompting or via cross-attentions in the transformer. At inference, the modifier is generated iteratively using the greedy approach.

plaining how the source pose  $A$  should be modified to obtain the target pose  $B$ . We rely on an auto-regressive model conditioned on the pose pair, which iteratively predicts the next word given the previous generated ones (see Fig. 6).

**Training phase.** Let  $T_{1:L}$  be the  $L$  tokens of the text modifier. An auto-regressive generative model seeks to predict the next token  $l + 1$  from the first  $l$  tokens  $T_{1:l}$ . Let  $p(\cdot|T_{1:l})$  be the predicted probability distribution over the vocabulary. The model is trained, via a cross-entropy loss, to maximize the probability of generating the ground-truth token  $T_{l+1}$  given previous ones:  $p(T_{l+1}|T_{1:l})$ .

To predict  $p(\cdot|T_{1:l})$ , the tokens  $T_{1:l}$  are first embedded, and positional encodings are injected. The result is fed to a series of transformer blocks [55], and projected into a space whose dimension is the vocabulary size  $q$ . Let  $\mathbf{t} \in \mathbb{R}^q$  denote the outcome. The probability distribution over the vocabulary for the next token  $p(\cdot|T_{1:l})$  could be obtained from  $\text{Softmax}(\mathbf{t})$ .

Transformer-based auto-regressive models can be trained efficiently using causal attention masks which, for each token  $l$ , prevent the network from attending all future tokens  $l' > l$ , in a single pass.

Now, how do poses come into the picture? Pose  $A$  and pose  $B$  are encoded using a shared encoder, and combined in the fusing module, which outputs a set of  $N$  ‘pose’ tokens. To condition the text generation on pose information, we experiment with two alternatives: those pose tokens can either be used for prompting, *i.e.*, added as extra tokens at

the beginning of the text modifier, or serve in cross-attention mechanisms within the text transformer.

**Inference phase.** For inference, we provide the model with the pose tokens and the special  $\langle \text{BOS} \rangle$  token which indicates the sequence beginning. We decode the output  $\mathbf{t}_2$  in a greedy fashion, *i.e.*, we predict the next token as the word that maximizes the negative log likelihood. We proceed iteratively, giving previously decoded tokens  $T_{1:l}$  to the model so to obtain the subsequent token  $l + 1$ , until the  $\langle \text{EOS} \rangle$  token (denoting the end of the sequence) is decoded.

**Evaluation metrics.** We resort to standard natural language metrics: BLEU-4 [40], Rouge-L [31] and METEOR [6], which measure different kinds of n-grams overlaps between the reference text and the generated one. Yet, we notice that these metrics do not reliably reflect the model quality for this task. Indeed, we only have one reference text and, given the initial pose, very different instructions can lead to the same result (*e.g.* “*lower your arm at your side*” and “*move your right hand next to your hip*”); it is not just a matter of formulation. Thus, we report the top-k R-precision metrics proposed in TM2T [19]: we use contrastive learning to train a joint embedding space for the modifiers and the concatenation of poses  $A$  and  $B$ , then we look at the ranking of the correct pose pair for each generated text within a set of 32 pose pairs. We also report reconstruction metrics on the pose generated thanks to our best model from Section 4 using the generated text. These added metrics assess the semantic correctness of the generated texts.



		R Precision $\uparrow$			NLP $\uparrow$			Reconstruction $\downarrow$ ( <i>best of 30</i> )		
		R@1	R@2	R@3	BLEU-4	ROUGE-L	METEOR	MPJE	MPVE	Geodesic
<b>Control measures</b>										
<i>random text</i>		3.13	6.25	9.38	7.11	26.33	26.88	225	185	9.07
<i>original text</i>		62.71	74.01	79.26	100.00	100.00	100.00	196	162	8.62
<b>Injection type (with/without pretraining)</b>										
<i>without</i>	prompt	3.63	7.10	10.73	9.74	<b>31.88</b>	27.72	226	184	8.94
	cross-attention	<b>6.78</b>	<b>12.27</b>	<b>17.35</b>	<b>10.62</b>	31.66	<b>28.74</b>	<b>220</b>	<b>180</b>	<b>8.85</b>
<i>with</i>	prompt	15.09	22.28	30.35	11.15	32.58	29.76	211	175	8.79
	cross-attention	<b>58.43</b>	<b>71.35</b>	<b>77.56</b>	<b>12.19</b>	<b>33.94</b>	<b>31.30</b>	<b>192</b>	<b>161</b>	<b>8.55</b>
<b>Data augmentations (with pretraining &amp; cross-attention injection)</b>										
no augmentation		58.43	71.35	77.56	<b>12.19</b>	33.94	<b>31.30</b>	192	161	8.55
with L/R flip		<b>60.69</b>	<b>71.51</b>	<b>78.85</b>	12.14	<b>34.02</b>	30.90	<b>189</b>	<b>159</b>	<b>8.54</b>
with paraphrases		53.91	67.72	74.98	10.56	33.07	30.15	194	162	8.65
with PoseMix		45.12	56.66	64.89	10.94	33.22	30.12	197	164	8.74

Table 6: **Correctional text generation results** for various pose injections and data augmentations. For reference, we also provide numbers for the ground-truth texts and an annotated text chosen at random.

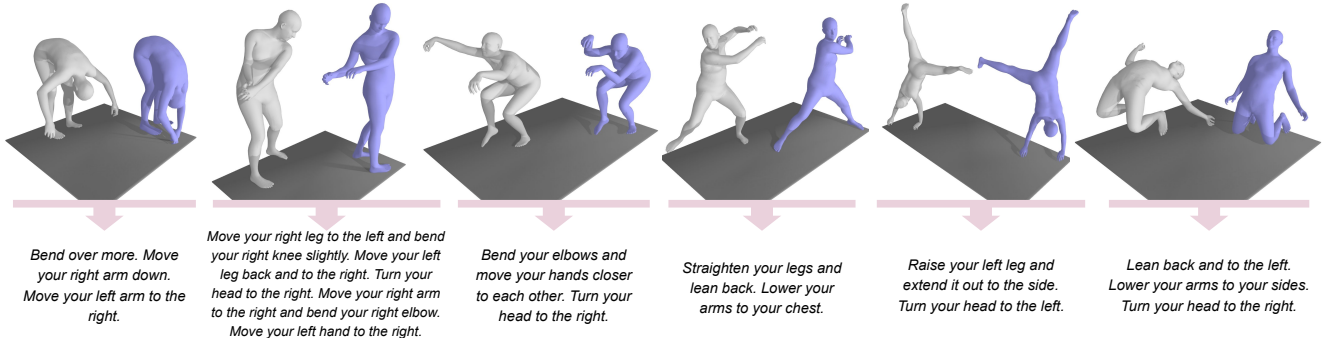


Figure 7: **Generated correctional texts** for PoseFix pose pairs (pose *A* is grey, pose *B* is purple). The original human annotations for these pose pairs are available in the supplementary material.

**Quantitative results** are presented in Table 6. We experiment with the same fusing module as before: TIRG [57], where the gating applied on the pair leading pose (pose *B*); thus using  $N = 1$ . We try prompting and cross-attention to inject the pose information in the text decoder, and found the latter to yield the best results. Pretraining on automatic modifiers significantly boosts the performance, *e.g.* with cross-attention injection, the R@2 increases from 12.27% to 71.35%. Regarding data augmentations, the left/right flip yields additional gains (+1.7% of average R Precision) with results close to those obtained with the ground-truth texts, both for R-precision and reconstruction. Even if the generated text does not have the same wording as the original text (low NLP metrics), combined with pose *A*, it achieves to produce a satisfactory pose  $\hat{B}$ , meaning that it carries the right correctional information. Of course, one should recall that the added metrics rely on imperfect models, which have their own limitations. Finally, we observe a decrease in performance with the paraphrases or the PoseMix settings: we hypothesize that these settings are harder than the regular one for this task, due to new words and formulations.

**Qualitative results.** Fig. 7 shows some generated texts.

The model is able to produce satisfying feedback, it generates egocentric relations (third and fourth examples) and groups indications by body part (second column). However, it tends to mix up pose *A* and *B* (last two examples). It also sometimes describes only a subset of the differences.

## 6. Conclusion

This paper lays the groundwork for investigating the challenge of correcting 3D human poses using natural language instructions. Going beyond existing methods that utilize language to model global motion or entire body poses, we aim to capture the subtle differences between pairs of body poses, which requires a new level of semantic understanding. For this purpose, we have introduced PoseFix, a novel dataset with paired poses and their corresponding correctional descriptions. We also presented promising results for two baselines which address the deriving tasks of text-based pose editing and correctional text generation.

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