Everybody Dance Now

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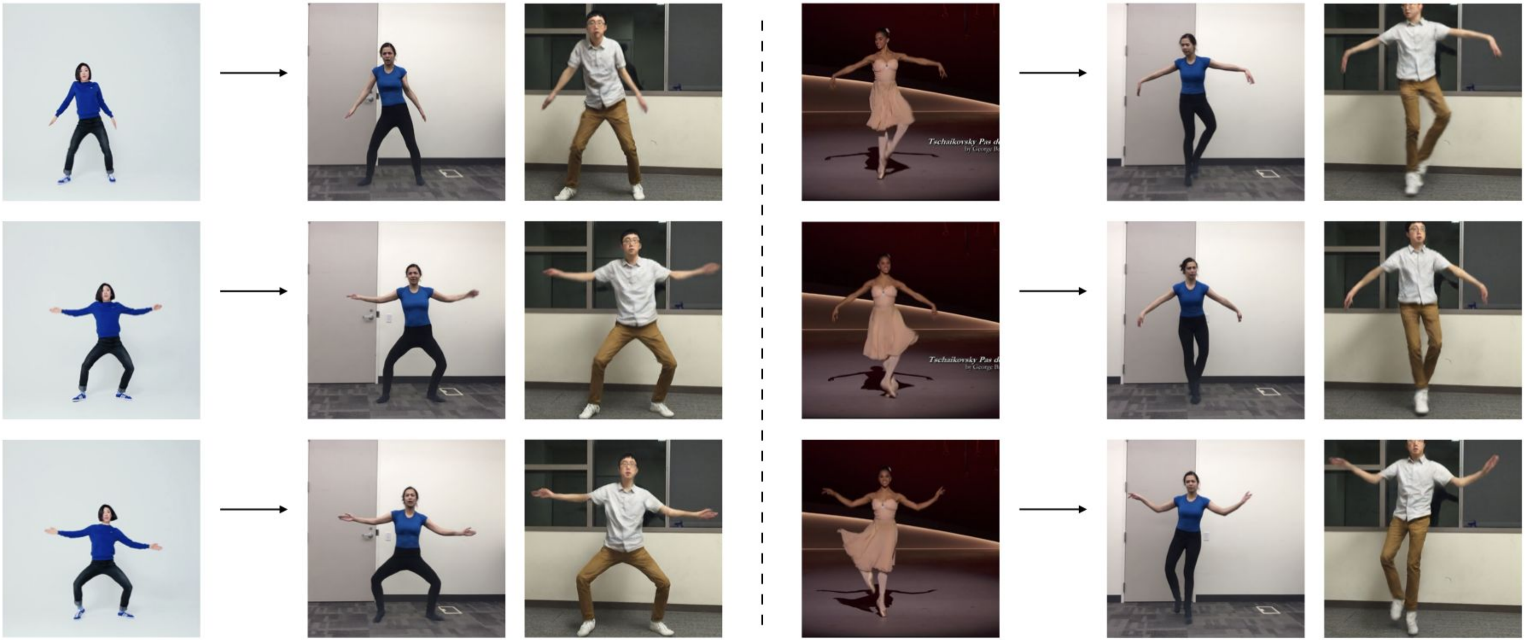
발표자 김연수

Contents



Source Subject | Target Subject 1 | Target Subject 2 | Source Subject | Target Subject 1 | Target Subject 2

Abstract

- This paper presents a simple method for **"do as I do" motion transfer**: **given a source video** of a person dancing, **we can transfer** that performance to a novel (amateur) tar- get after only a few minutes of **the target subject performing standard moves.**
- We approach this problem as **video-to- video translation using pose as an intermediate representation.**
- Approach
  - **extract poses** from the source
  - apply the learned pose-to-appearance **mapping** to generate the target
  - predict two consecutive frames for **temporally coherent** video results
  - separate pipeline for realistic **face synthesis**
- more contribution
  - fake video detection
  - release a dataset

Abstract

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Our generator and discriminator architectures follow that presented by Wang et al. [41]. The fake-detector architectures matches that of the discriminator with a final fully connected layer.

Introduction

- GOAL

    → corresponds to frames of the ***target*** subject performing the same motions

    → we transfer motion between these **subjects**(source, target) by learning a simple **video-to-video translation.**

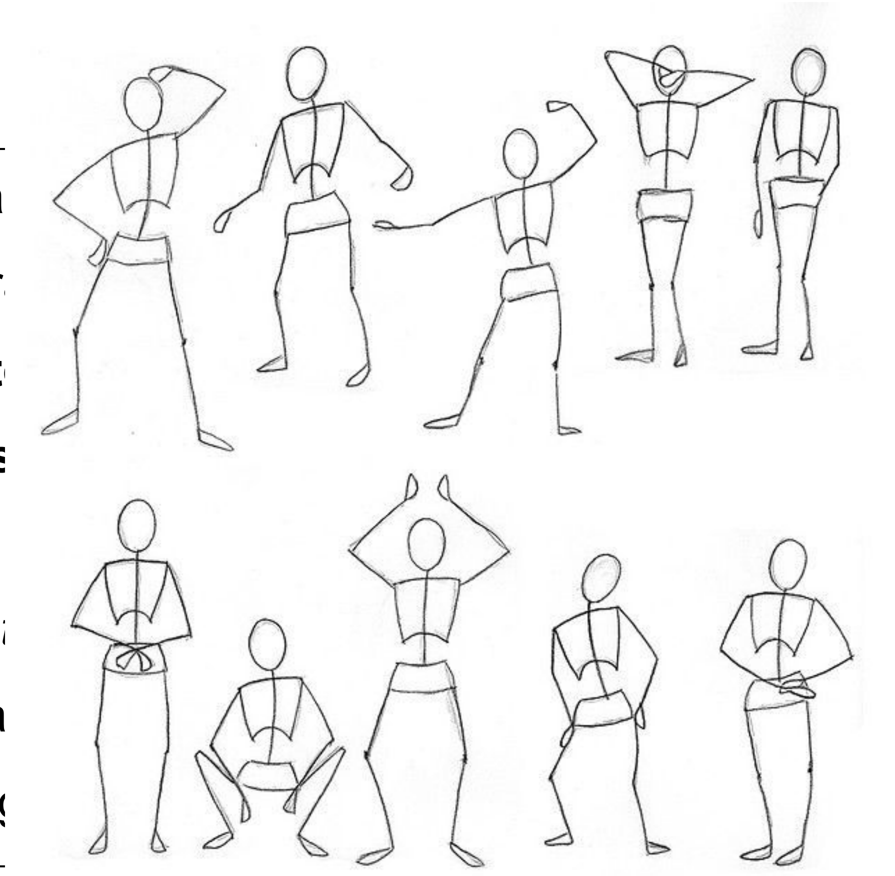
    → to discover an **image-to-image translation** between the source and target **sets. (frame-by-frame manner)**

    BUT, we do not have corresponding pairs of images of the two subjects performing the same motions to supervise learning this translation.

Introduction

- We observe that **keypoint-based pose** preserves motion signatures over time while abstracting away as much subject identity as possible and **can serve as an intermediate representation between any two subjects.**
- We therefore **use pose stick figures** obtained from off-the-shelf human pose detectors, such as **OpenPose**, as an intermediate representation for *frame-to-frame transfer*, as shown in Figure 2.
- We then learn an image-to-image translation model between pose stick figures and images of our target person.

Introduction



- We observe tha… signatures over time while abstr…ossible and **can serve as an int… two subjects.**
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Introduction

- We ob … s over time w … nd **can serve … cts.**
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- We th … tick figure…

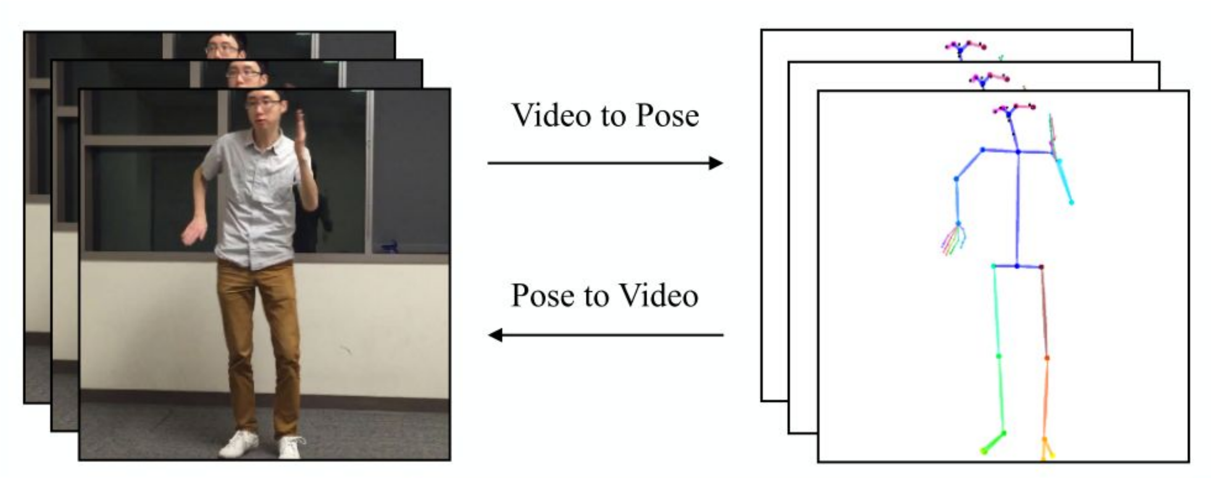

Figure 2: Our method creates correspondences by detecting poses in video frames (Video to Pose) and then learns to generate images of the target subject from the estimated pose (Pose to Video).

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Related Work - OpenPose, DensePose

Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields *

Zhe Cao Tomas Simon Shih-En Wei Yaser Sheikh
The Robotics Institute, Carnegie Mellon University
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OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields

Zhe Cao, *Student Member, IEEE,* Gines Hidalgo, *Student Member, IEEE,*
Tomas Simon, Shih-En Wei, and Yaser Sheikh

Related Work - OpenPose

Pose Estimation

- Top-Down Approach
- **Bottom-up Approach**
  - 한 장의 사진에서 먼저 각각의 관절에 대한 정보를 찾고 이 관절이 어떤 관절과 연결되는지 찾아 하나의 사람으로 만들어 주는 것
  - robustness를 보장해주면서, 많은 수 의 사람들이 등장해도 한 명일때와 다르지 않게 처리가 가능

https://reading-cv-paper.tistory.com/entry/TPAMI-OpenPose-Realtime-Multi-Person-2D-Pose-Estimation-using-Part-Affinity-Fields

Related Work - OpenPose, DensePose

Pose Estimation

- Top-Down Approach
- **Bottom-up Approach**

(a) Input Image (b) Part Confidence Maps (c) Part Affinity Fields (d) Bipartite Matching (e) Parsing Results

https://reading-cv-paper.tistory.com/entry/TPAMI-OpenPose-Realtime-Multi-Person-2D-Pose-Estimation-using-Part-Affinity-Fields

Related Work - Pix2PixHD

High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs

Ting-Chun Wang[1] Ming-Yu Liu[1] Jun-Yan Zhu[2] Andrew Tao[1] Jan Kautz[1] Bryan Catanzaro[1]
[1] NVIDIA Corporation [2] UC Berkeley

https://haawron.tistory.com/26

Method

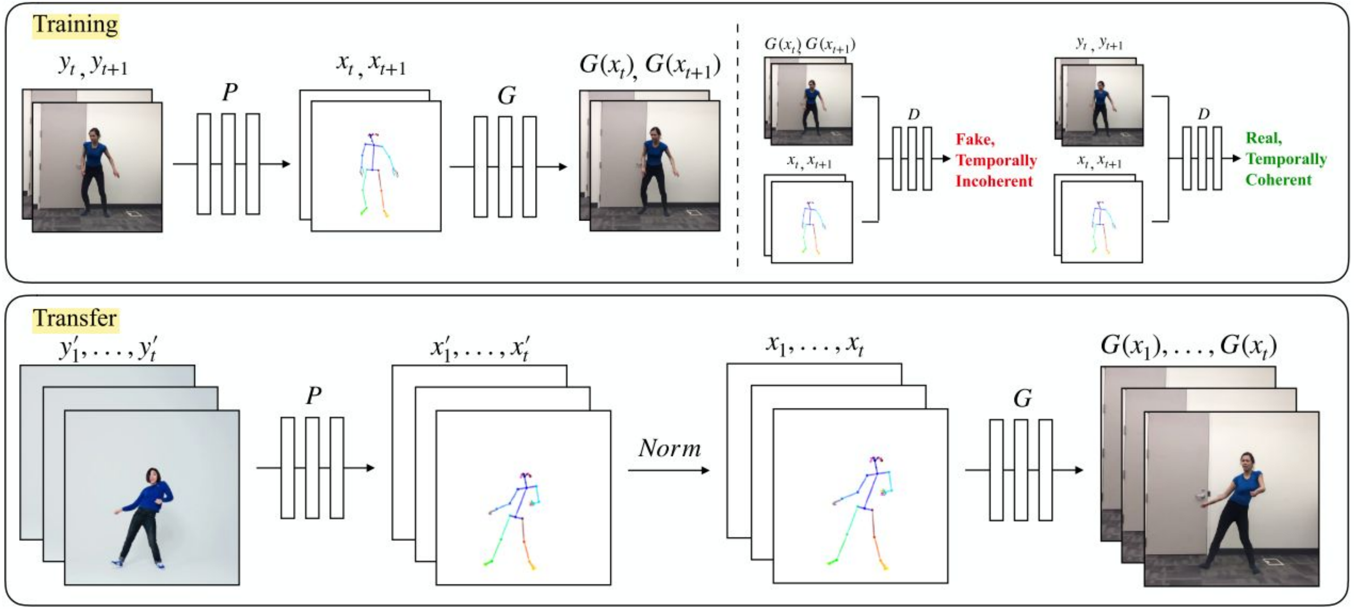


Figure 3: (Top) **Training**: Our model uses a pose detector P to create pose stick figures from video frames of the target subject. We learn the mapping G alongside an adversarial discriminator D which attempts to distinguish between the "real" correspondences $(x_t, x_{t+1}), (y_t, y_{t+1})$ and the "fake" sequence $(x_t, x_{t+1}), (G(x_t), G(x_{t+1}))$. (Bottom) **Transfer**: We use a pose detector P to obtain pose joints for the source person that are transformed by our normalization process $Norm$ into joints for the target person for which pose stick figures are created. Then we apply the trained mapping G.

Method

Pose Encoding and Normalization

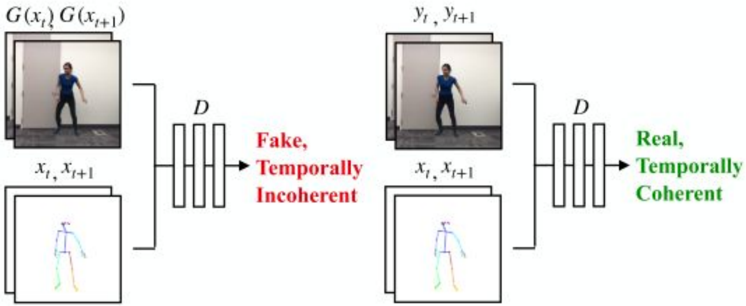
- Encoding body poses : use pose detector ***P*** **(OpenPose)**
  - estimates 2D x,y joint coordinates
- Global pose normalization
  - Why? → subjects may **have different limb proportions**
  - **it may be necessary to transform the pose keypoints of the source** person so that they appear in accordance with the target person's body shape and location as in the **Transfer section**
  - We find this transformation by analyzing **the heights and ankle positions for the poses** of each subject and use a linear mapping between the closest and farthest ankle po- sitions in both videos. After gathering these positions, we calculate **the scale and translation for each frame** based on its corresponding pose detection

Method

Pose to Video Translation

- Our video synthesis method is based off of an **adversarial single frame generation** process
- For our purposes, **G synthesizes** images of a person given a **pose stick figure**
- Such **single-frame image-to-image translation methods**
- Add a learned model of **temporal coherence** as well as a module for **high resolution face generation**

Method



Pose to Video Translation

- Temporal Smoothing
  - the discriminator is now tasked with determining both the difference in realism and temporal coherence between the “fake” sequence (x_{t−1}, x_t, G(x_{t−1}), G(x_t)) and “real” sequence (xt−1, xt, yt−1, yt).
  - $$\mathcal{L}_{\text{smooth}}(G, D) = \mathbb{E}_{(x,y)}[\log D(x_t, x_{t+1}, y_t, y_{t+1})] + \mathbb{E}_x[\log(1 - D(x_t, x_{t+1}, G(x_t), G(x_{t+1}))] \qquad (1)$$
- Face GAN
  - We add a specialized GAN setup to **add more detail and realism to the face region**
  - $$\mathcal{L}_{\text{face}}(G_f, D_f) = \mathbb{E}_{(x_F, y_F)}[\log D_f(x_F, y_F)] + \mathbb{E}_{x_F}[\log(1 - D_f(x_F, G(x)_F + r))].$$

Method

Full Objective (To train)

- We employ training in stages where the full image GAN is optimized separately from the specialized face GAN
-

$$\min_G((\max_{D_i}\sum_{k_i}\mathcal{L}_{\text{smooth}}(G,D_k))+\lambda_{FM}\sum_{k_i}\mathcal{L}_{\text{FM}}(G,D_k)$$
$$+\lambda_P(\mathcal{L}_P(G(x_{t-1}),y_{t-1})+\mathcal{L}_P(G(x_t),y_t))) \quad (3)$$

ting. We follow the progressive learning schedule from pix2pixHD and learn to synthesize at 512×256 at the first (global) stage, and then upsample to 1024×512 at the second (local) stage. For predicting face residuals, we use the global generator of pix2pixHD and a single 70×70 Patch-GAN discriminator [16]. We set hyperparameters $\lambda_P = 5$ and $\lambda_{VGG} = 10$ during the global and local training stages respectively. For the dataset collected in Section 4.1, we trained the global stage for 5 epochs, the local stage for 30 epochs, and the face GAN for 5 epochs.

Method

[Transfer] we divide our pipeline into three(3) stages

1. **pose detection** → OpenPose
2. global pose normalization → accounts for differences between the source and target **body shapes and locations within the frame**
3. target person의 합성된 video 생성 → mapping from normalized pose stick figures to the target subject

Experiments

Ablation conditions

- Frame-by-frame synthesis (FBF)
- Temporal smoothing (FBF+TS)
- Our model (FBF+TS+FG)

Evaluation metrics

- SSIM. Struc- tural Similarity
- LPIPS Learned Perceptual Im- age Patch Similarity

Experiments

Region	Metric	FBF	FBF+TS	FBF+TS+FG
Face	SSIM	0.784	0.811	**0.816**
	LPIPS	0.045	0.039	**0.036**
Body	SSIM	0.828	**0.838**	**0.838**
	LPIPS	0.057	0.051	**0.050**

(a) Metric comparison for synthesized face (top) and full-body (bottom) regions. Metrics are averaged over the 5 subjects. For SSIM higher is better. For LPIPS lower is better.

Condition	1	2	3	4	5	Total
FBF	54.1%	69.7%	62.4%	53.8%	60.0%	58.8%
FBF+TS	59.6%	56.4%	50.3%	53.0%	53.1%	53.9%

(b) Perceptual study results for subjects 1 through 5 and in total average. We report the percentage of time participants chose **our** method as more realistic than the ablated conditions.

Table 3: Ablation studies. We compare frame-by-frame synthesis (FBF), adding temporal smoothing (FBF+TS) and our final model with temporal smoothing and Face GAN modules (FBF+TS+FG).

Condition	1	2	3	4	5	Total
Prefer FBF+TS	60.5%	62%	57.5%	50%	62.5%	58.5%

Table 4: Comparison of our method without Face GAN (FBF+TS) to the FBF ablation for subjects 1 through 5 and in total average. We report the percentage of time participants chose the FBF+TS ablation over the FBF ablation.

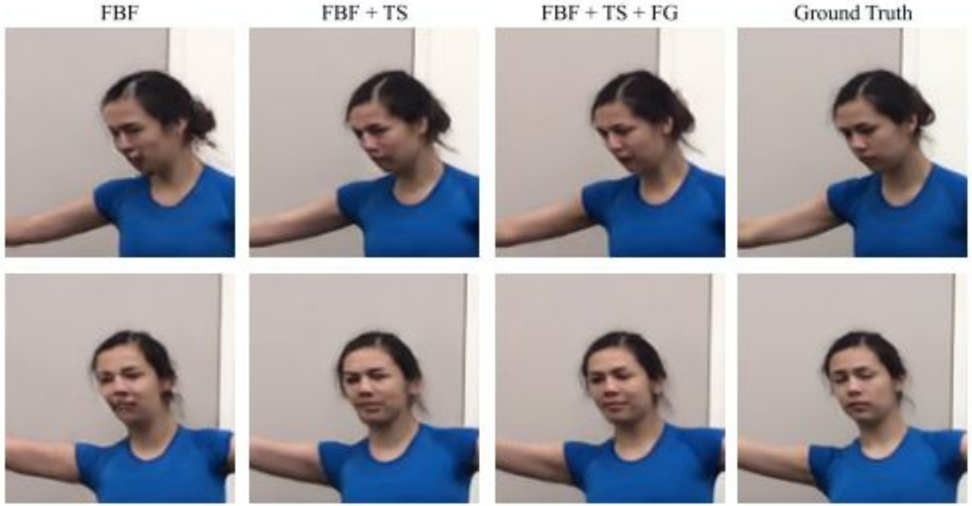


Figure 6: Face image comparison on held-out data. We compare frame-by-frame synthesis (FBF), adding temporal smoothing (FBF+TS) and our full model (FBF+TS+FG).

Limitations and Discussion

- Further work could focus on improving results **by combining target videos with different clothing or scene lighting**, improving pose detection sys- tems, and **mitigating the artifacts** caused by high frequency textures in loose/wrinkled clothing or hair.
- Future work could focus on the **train- ing data**, i.e. what poses and how many are needed to learn a effective model. This area relates to work on understanding which training examples are most influential