Why you walk like that: Inferring Body Conditions from Single Gait Cycle

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Figure 1: Gait manifold. A scattered point represents a single gait cycle. Similar gaits are placed nearby.

ABSTRACT

Gait is a key barometer to analyze human body conditions. We propose a personalized gait analysis framework which can diagnose a possible muscularskeletal disorders with a single gait cycle. Our framework built over a gait manifold which reveals the principle kinematic characteristics in the temporal pose sequence. Body parameters such as muscle, skeleton, and joint limits for an arbitrary gait cycle can be approximated by measuring similarity in the small latent space. We present a physical gait simulator to enrich the gait space paired with the body conditions.

CCS CONCEPTS

• **Computing methodologies** → **Learning latent representations**; **Physical simulation**.

KEYWORDS

character animation, gait analysis, motion manifold, physics-based simulation

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1 INTRODUCTION

Walking is a representative movement that shows the mobility and balance of the body. Physical and behavioral characteristics, such as height, weight, body structure, muscle strength, and even fatigue and mood, cause a variety of gait patterns. As gait patterns reflect personal body characteristics, sometimes people can identify each other just by looking at walking styles.

Motion analysis using a camera or motion capture system have been introduced to extract key features that affect behaviors. There have been attempts by the medical community to diagnose musculoskeletal disorders of patients through non-invasive gait analysis. However, rather than utilizing all the kinematic information (joint orientation, cadence, walking speed, etc.) of the capture data, only the simple hand-crafted features (maximum knee flexion angle, crouch angle in the middle of the stance phase, etc.) are used. The technical challenges come from the high dimensionality of the temporal pose sequences and the body parameters. Lack of fully observed pairs between gait patterns and body conditions also increases the difficulty of a comprehensive analysis.

In this paper, we present a novel deep learning based framework for the personalized gait analysis. We propose a gait manifold to find out strong correlation between gait patterns and body conditions. In this compressed space, thousands of dimensions of gait sequence is represented in 16 dimensions, making it possible to measure similarity between motions. Our gait manifold is densely represent the diversity of the gait with bootstrapping via physical simulation as well as clinical data captured in hospital. We construct a well-balanced dataset consists of the pair of body features $\mathcal{F}$ and gait cycles C thanks to gait simulator that is responsive to given musculoskeletal conditions.

2 OUR APPROACH

The goal of our research is to learn the physical body specification from a single gait cycle. Our main idea is built on the intuition that gait analysis can be treated as an opposite of gait simulation which generates accurate motions under varying body conditions. We simulate the gait patterns induced by musculoskeletal conditions and joint limitations, and reversely infer body parameters through similarity between motions.

2.1 Gait manifold

We employ a neural network based on the Wasserstein Auto Encoder [Tolstikhin et al. 2017], which can lower the dimension of motion while maintaining its expressiveness. Gait cycle is a time-series pose set, each of which is represented as the joint orientations. We use a human character with lower body that has 11 joints. The gait data is normalized as 30 frames sequence, starting with a left-footed wheel-strike, until contact with the ground with the right foot and then turning the left foot again. Not only normal gaits, but also motion capture data of patients with cerebral palsy collected for clinical purposes are used. These patients have musculoskeletal disorders that cause pathologic motion such as pelvis tilt, femoral anteversion, knee flexion, and intoeing. Our network learns the key kinematic features from a gait cycle through compression-reconstruction processes. The loss of the network includes four component:

$$E = E_{\text{reconstruct}} + E_{\text{mmd}} + E_{\text{root}} + E_{\text{position}}. \tag{1}$$

where E_{mmd} (Maximum mean discrepancy) forces the distribution in the original gait space to be maintained in the manifold. We add forward kinematics layer on the network that computes 3D joint positions from input vectors to increase accuracy and prevent blurriness of the reconstruction. Low-dimensional gait embeddings can be used to measure the similarity and interrelationship of motion.

2.2 Bootstrapping with physics simulation

Clinical data is highly biased because it captures the severe patients to evaluate the case-controlled of the surgery. We bootstrap the gait space from simulated gait which is parameterized with major lower body conditions. Our controller consists of a muscle actuated system with 172 muscles of the lower body. Deep Reinforcement Learning (DRL) have been successfully incorporated with the physics-based simulation under the variety of the constraints, such as muscles [Lee et al. 2019] and bone shapes [Won and Lee 2019]. We simulate the gait cycle according to the body parameters such as muscle length, joint range of motion (ROM) limitation of the femur and the degree of pelvis tilt. Ten major muscles are included in the body parameters (Left and Right *Psoas Major, Biceps Femoris, Rectus Femoris, Soleus, Tibialis*). The total body condition parameters is 15.

3 RESULTS & DISCUSSION

Our gait dataset for learning gait manifold consists of 20000 simulated gait cycle and 200 clinical purpose motion captured data. We adopt UMAP [McInnes et al. 2018] to visualize the gait manifold in 2D space while maintaining its non-linearity. We recommend that readers refer to supplementary video for the detailed results.

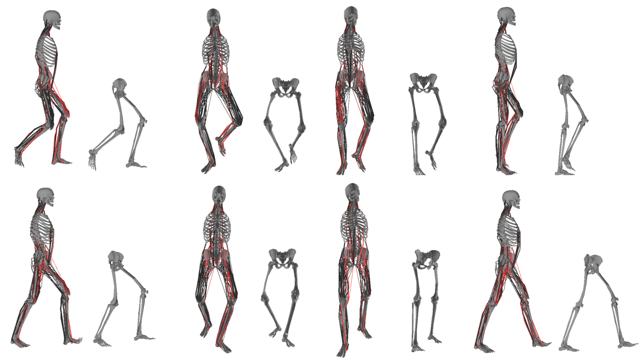

Figure 2: Comparison with a gait cycle and its simulated result with inferred body conditions.

Figure 1 shows that similar motions located at a close distance on the manifold. We infer the physical conditions of a gait by measuring the similarity between embeddings. When re-simulated with inferred body parameters, a gait cycle similar to the original data is generated (Figure 2). We now

We demonstrated the motion interpolation to prove that gait manifold can be used as a substitute for high-dimensional original gait space. It is possible to create a reasonable gait after mixing two different gait cycles on the gait manifold with linear interpolation. We compared our network with typical Variational Auto Encoder (VAE). After encoding-decoding procedure the original representation, our network showed 0.7cm loss with Euclidean distance for each joint, while VAE was 7.1cm.

Our future direction is to increase the number of parameters for simulation so that we can analyze more pathologies as well as musculoskeletal disorders in the lower extremities. The more we can model and simulate beyond the musculoskeletal system (e.g., nervous system, mechanisms of the growth and aging), the more likely we are to discover various diseases. Measuring consistency with medical diagnosis can increase the practicality of the proposed algorithm. Inferring human states with vision-based devices rather than motion capture is also an interesting direction to improve accessibility.

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