Simulation Report

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May 2024

1 Introduction

The project's objective is to alter the skin's shape using implicit Skinning, which employs HRBF (Hermite Radial Basis Function). In Vaillant (2013), this method enables a more authentic treatment of skin deformations at joints, hence minimising the occurrence of the candy wrapper effect and other abnormal shape distortions commonly observed in conventional skins.

2 Literature Review

2.1 category

Character animation has consistently played a crucial role in the creation of various forms of media, particularly animation. Utilising skin simulation techniques enhances the ability to replicate lifelike character skin effects. The technique's complexity and significance have rendered it a prominent subject of study in the realm of computer graphics. The issues that require attention The challenges faced by skin deformation techniques can be classified into three main categoriesRumman and Fratarcangeli (2016): generating skin deformations of high quality, replicating skin contact in reaction to collisions, and producing secondary motion effects such as flesh jiggling during character movement.

There are multiple categories for categorising skin simulation techniques, as individuals have varied viewpoints on how to define them based on the specific item or concept that the approach addresses. The realisation principle can be categorised into three main techniques: skeleton-based deformation (including geometry and example-based skinning), volume-preserving skinning, and physics-based skinning methods. This classification is based on the work of Rumman and Fratarcangeli (2016) in the field of skin deformation. An alternative viewpoint proposes that we can classify it into three approaches Chaudhry et al. (2010): surface-based, space-based, and physics-based.

I'd rather use the principle view method to describe techniques across the entire field. In reality, people often combine these methods instead of using them separately.

2.2 Category of interpretation

2.2.1 Skeleton-based deformation

The skeleton-based deformation approach will exclusively concentrate on the correlation between the skeleton and mesh. This technique does not consider internal structural changes and additional secondary motions, hence it lacks attention to secondary motions and seems less realistic. Surface-based techniques are the most often utilised in computer animation production due to their simplicity compared to volume-preserving and physics-based skinning methods. Additionally, these techniques create appropriate skin deformations.

There are two approaches: the geometric method and the example-based method, which can also be referred to as data-driven methodologies. The first method employs a geometrical approach to directly compute the correlation between the bones and skin. For example, the joint-based type approach commonly employs linear blend skinning (LBS). The use of dual quaternions (DQs) effectively overcomes the problem of the "candy-wrapper" issue. However, it also reveals a distinct artefact referred to as the "joint-bulging artefact." This research utilises the HRBF field to alleviate each of these concerns by employing a correction technique.

2.2.2 Example-based skinning method

Another approach is the example-based skinning method. These methods take a series of sculpted example poses as input and interpolate them to obtain the desired deformation. The typical methods are Lewis et al. (2000)PSD, Rhee et al. (2006) WPSD, single-weight enveloping(Mohr and Gleicher (2003)), multi weight enveloping(Wang and Phillips (2002)).

Volume preservation techniques allow artists to correct changes in volume caused by skin deformation procedures, such as linear blend skinning (LBS), by adding extra bulges and wrinkles. Cage-based skinning techniques and the Free-Form Deformation (FFD) method might be regarded as part of ways for preserving volume.

2.2.3 Physics-based skinning method

Physics-based skinning approaches effectively tackle the three concerns associated with skin deformation, both in theory and in practice. It is superior to a purely kinematic method. We employ mass-spring systems to simulate soft tissue. It is plagued with instability. This can lead to problems with overshooting during operations. In addition, mass-spring systems often don't work very accurately because they depend too much on topology and don't have a strong basis in elasticity theory.

Finite element methods (FEM) simplify elastic material modeling by consolidating masses, internal forces, and external forces at the vertices. While the mass spring system has limited applicability, the finite element method (FEM) is applicable to a wide range of materials. However, the Finite Element Method (FEM) is both resource-intensive and challenging to include.

The system relies on anatomical features and independently replicates the behaviour of muscles; however, the computing load is excessively large. The intricacies of muscle behavior are highly complex, and the current simulation based on specific physics principles is insufficient in its comprehensiveness. The physically-based technique necessitates the calculation of contractile muscle forces and the depiction of dynamic muscle shape during contraction. The mass-spring system, the finite element method (FEM), and the finite volume method are all capable of accomplishing this.

2.2.4 machine Learning

As stated by Seo et al. (2021) in their study, traditional simulation techniques based on skeleton-driven approaches rely on linear transformations, which pose challenges in accurately representing nonlinear deformations in soft tissue. Physically-based approaches, which use voxels to represent fat in skeletal muscles, calculate physical characteristics but need excessively high processing expenses. Utilising data-driven methodologies is typically more advantageous in accurately representing the realistic impacts of soft tissue deformation. Due to the advancement of shape datasets obtained from real individuals at high resolution, this technique is more likely to achieve high performance. However, its primary use is to forecast and capture human action poses. Soft body might be regarded as a variable in certain research studies. In the SMPL procedure Pons-Moll et al. (2015), the argument dmpl is used to describe the soft tissue characteristic.

The authors propose a technique that utilises learning algorithms to address the issue of dynamic skin deformation. The essence of their research revolves around a recurrent neural network that acquires the ability to forecast the non-linear, dynamics-dependent alteration in shape over time using pre-existing data on mesh deformation sequences. Their network also acquires the ability to anticipate the fluctuations in skin dynamics among individuals of diverse body types. Upon completion of the training process, the network is capable of generating lifelike and superior skin movements that are tailored to an individual in real-time. They achieve findings that greatly reduce computational time while keeping prediction quality that is comparable to state-of-the-art outcomes.

3 Theoretical Background

3.1 RBF deformation

Computer graphics and machine learning frequently use RBF deformation, also known as Radial Basis Function (RBF) deformation. In Hacker Noon (2023), a radial basis function is a mathematical function that assigns a real-valued output to a real-valued input based on the distance between the input value and a certain point in space. After obtaining the radius function, we can calculate a series of values that allow us to modify the mesh by accurately controlling the value and making necessary adjustments to the vertices. Created. To create a smooth interpolation between values only known at specified locations, we can use Radial Basis Functions (RBFs). We define "radial" as the distance between a fixed location in three-dimensional space and another position where we need to evaluate a specific quantity. This technique utilises radial basis functions to interpolate and spatially manipulate data points using a predefined set of control points. The range of applications varies depending on the selected type of RBF.

3.2 Hermite Radial Basis Function

When doing data interpolation, HRBF (Hermite Radial Basis Function) takes into account both the positional data and the derivative information, often the first-order derivative (gradient). This approach allows HRBF to more effectively maintain the form features of the original data in modelling and interpolation tasks. The utilisation of HRBF, represented by a cubic function x^3, is especially well-suited for deformations that include delicate manipulation and a responsive reaction, such as those found in skin.

3.2.1 Pros and Limitations of RBF

The RBF deformation technique is capable of effectively and seamlessly handling a wide range of data points, particularly those that are non-linearly distributed within the dataset. This results in a natural and cohesive deformation effect.

Great versatility: You can achieve intricate spatial distortion by just manipulating a few key control points.

The computational cost of RBF deformation grows significantly as the number of control points increases, particularly when working with large 3D models.

4 Implementation Details

4.1 build static HRBF field

4.1.1 culling

Just as the article said, Vaillant et al. (2013) Firstly, culling the unnecessary control vertices by using the culling function.

Culling function: $h < \frac{(v_k - b_i^0)^T (b_i^1 - b_i^0)}{||b_i^1 - b_i^0||^2} < 1 - h$

In the given function, b_i^0 represents the current joint, which corresponds to the starting point of a bone. On the other hand, b_i^1 represents the child bone, which corresponds to a bone's ending point. The value of h will be used to identify the vertices that can be considered control points.

4.1.2 build the first HRBF field

Firstly, it is essential to reconstruct a distance field in order to precisely represent the relationship between vertices and control points in the existing model. Once the control points have been processed, all points will be inputted into the equation, and we will then solve the equation to obtain the values of α and β. Subsequently, we compute the initial HRBF values for each individual point. Employ HRBF to generate a distance field that assigns a value of 0 (specifically, 0.5 in this instance) when the target is precisely situated on the desired surface. Alternatively, we can interpret this as having an HRBF value of 0 for the vertices on the surface.

The main idea behind HRBF (Hierarchical Radial Basis Function) is that it has a formula with unknown coefficients alpha and beta, as well as control points and vertices that are known and unknown. The spatial orientation and consistency orientation establish a framework for the coefficients alpha and beta. We explain the relationship between vertices and control points. We employ a coefficient to ascertain the HRBF value and gradient. We will use this coefficient to compute the updated position.

The individual HRBF fields, as described in the work of Vaillant (2013), provide the essential capability to obtain the solutions for α (or λ) and β, and subsequently compute the value and gradient.

$$d_i(x) = \sum_{k=1}^{m} (\lambda_k \phi(||x - v_k||) + \beta_k^T \nabla \phi(||x - v_k||))$$

4.1.3 compact support

Once we obtain the HRBF field, we must utilise the compact support function to compute the ultimate HRBF values.

Compact support: $f_i(x) = t_r(d_i(x))$

$$t_r(x) = \begin{cases} 1 & \text{if } x < -r \\ 0 & \text{if } x > r \\ \frac{-3}{16}\left(\frac{x}{r}\right)^5 + \frac{5}{8}\left(\frac{x}{r}\right)^3 - \frac{15}{16}\frac{x}{r} + \frac{1}{2} & \text{otherwise} \end{cases}$$

In Vaillant (2013), the r is the distance between the bone and the farthest sampling point used for reconstruction.

4.1.4 Global field

In the preceding phases, we obtained the individual HRBF values. The global field can be obtained by utilising the union operator.

4.2 corrections

Update vertices positions:

$v_i \leftarrow v_i + \sigma(f(v_i) - iso_i)\frac{\nabla f(v_i)}{\|\nabla f(v_i)\|^2}$

After referencing Autodesk (2024) and Vaillant (2022), I utilised Maya's skinCluster approach as the basis for the traditional skinning process. The LBS technique is the primary method used for skinning. The HRBF method is an optimisation methodology that focuses on optimising and rectifying vertices. The displacement value is derived by multiplying the HRBF value with the gradient.

Maya's skin triggers the deform function for each frame. The displacement of the vertices is calculated using the usual skinning approach called linear blend skinning (LBS). We calculate the revised transformation for the new bone position, assuming that it will be located on the surface when the HRBF value is 0 (roughly 0.5). Ultimately, we rectify the result by implementing LBS via HRBF. We have completely relocated the vertex position for every frame.

5 Results and Discussion

I have developed a rudimentary Maya plugin Autodesk (2024) that generates fundamental joints, mesh, and bindings by scripting. You can download the plugin and run it in your Maya environment. While replacing the deformer, I maintained the camera view and target. I employed the HRBF technique to rectify the loss of volume and preserve the initial relative connection between the mesh and bone. The corrections made by the HRBF method successfully restored the volume that distortions had partially lost.

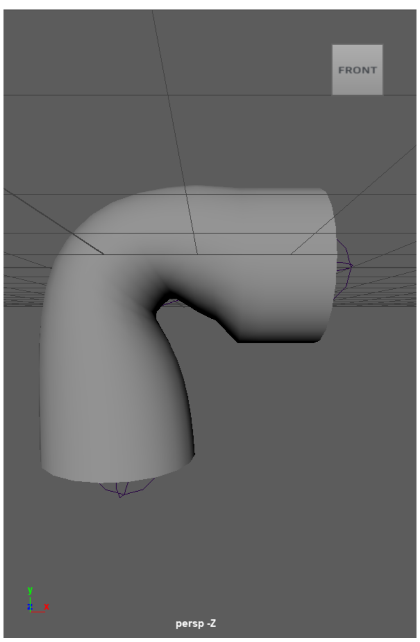

Figure 1: LBS default method

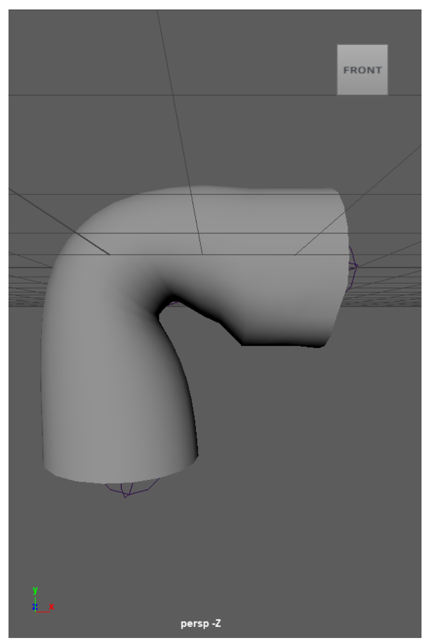

Figure 2: HRBF method

Time constraints prevented us from directly using the interpolation method to calculate the correction values. Instead, we directly computed the value

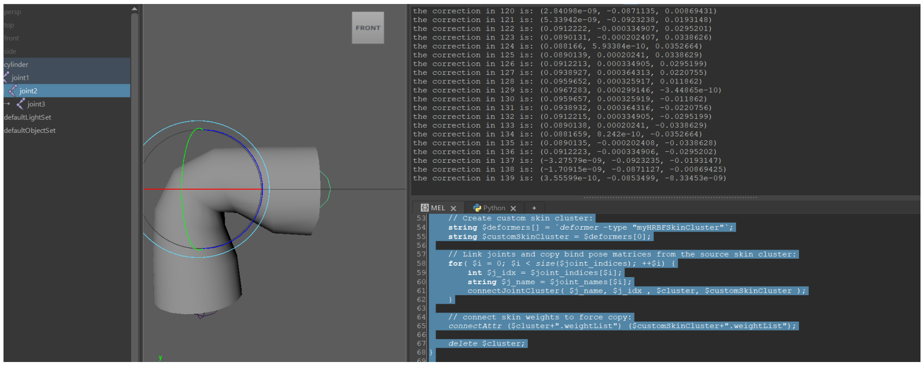

Figure 3: correction value

that would yield the difference by selecting a reduced number of samples. We intended this approach to enhance the smoothness of the final surface. In order to store the data effectively, it is important to select an appropriate spatial structure. In the study referenced as Vaillant et al. (2013), a resolution of 128^3 was used.

We only used the concatenation operation to compute the global distance field. However, we must include collision detection to ascertain the need for adjustments based on the contact volume detection angle.

Currently, we use all vertices as control points. While this method yields accurate results, it is somewhat slow. You can employ poisson sampling or other sampling techniques indicated in the referenced work Vaillant et al. (2013) to expedite the process.

Finally I printed the corrected values to quantitatively observe the final resultant effect, as in the contents of Figure 3.

6 Conclusion

Skin deformation, a crucial technique in computer graphics, has a rich history of advancements in conventional approaches to create novel methods for addressing three significant challenges. It is frequently employed in conjunction with multiple techniques to attain superior outcomes while reducing costs. Recent advancements in machine learning techniques for skin dynamics involve employing a data-driven methodology to obtain more accurate and complex non-linear skin deformation.

My project simply applies the fundamental HRBF-generated distance field to manipulate the skin's shape. There is still much room for improvement in terms of computational speed and performance optimisation. However, it plays a critical role as a more sophisticated geometric method for studying skin deformation. As a more advanced geometrical method for my learning in the direction of skin deformation there is an important help and role.

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