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Chapter X

Learning 3D Face Deformation Model: Methods and Applications

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Abstract

This chapter presents a unified *framework for* machine-learning-based facial deformation modeling, analysis *and* synthesis. *It enables flexible, robust face motion analysis and natural synthesis, based on a* compact *face motion model learned from motion capture data. This model, called* Motion Units *(MUs), captures the characteristics of real facial motion. The MU space can be used to constrain noisy low-level motion estimation for robust facial motion analysis. For synthesis, a face model can be deformed by adjusting the weights of MUs. The weights can also be used as visual features to learn* *audio-to-visual mapping using neural networks for real-time, speech-driven, 3D face animation. Moreover, the framework includes parts-based MUs because of the local facial motion and an interpolation scheme to adapt MUs to arbitrary face geometry and mesh topology. Experiments show we can achieve natural face animation and robust non-rigid face tracking in our framework.*

Introduction

A synthetic human face provides an effective solution for delivering and visualizing information related to the human face. A realistic, talking face is useful for many applications: visual telecommunication (Aizawa & Huang, 1995), virtual environments (Leung et al., 2000), and synthetic agents (Pandzic, Ostermann & Millen, 1999).

One of the key issues of 3D face analysis (tracking and recognition) and synthesis (animation) is to model both temporal and spatial facial deformation. Traditionally, spatial face deformation is controlled by certain facial deformation control models and the dynamics of the control models define the temporal deformation. However, facial deformation is complex and often includes subtle expressional variations. Furthermore, people are very sensitive to facial appearance. Therefore, traditional models usually require extensive manual adjustment for plausible animation. Recently, the advance of motion capture techniques has sparked data-driven methods (e.g., Guenter et al., 1998). These techniques achieve realistic animation by using real face motion data to drive 3D face animation. However, the basic data-driven methods are inherently cumbersome because they require a large amount of data for producing each animation. Besides, it is difficult to use them for facial motion analysis.

More recently, machine learning techniques have been used to learn *compact* and *flexible* face deformation models from motion capture data. The learned models have been shown to be useful for realistic face motion synthesis and efficient face motion analysis. In order to allow machine-learning-based approaches to address the problems of facial deformation, analysis and synthesis in a systematic way, a unified framework is demanded. The unified framework needs to address the following problems: (1) how to learn a compact model from motion capture data for 3D face deformation; and (2) how to use the model for robust facial motion analysis and flexible animation.

In this chapter, we present a unified machine-learning-based framework on facial deformation modeling, facial motion analysis and synthesis. The framework is illustrated in Figure 1. In this framework, we first learn from extensive

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