CONNECTIONI ST MODELS I N MULTI MODAL HUMAN-COMPUTER I NTERACTI ON

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Abstract

We present an overview of our laboratories' research on h several connectionist Multimodal Human-Computer Interfaces. By exploiting Large Vocabulary Confl available channels of human communication we aim eous speech recogrincrease flexibility, robustness, and natural ness of huceptrons (MLP), man-computer interaction. The information sources we proig Vector cess include Speech-, Character-, and Cesture Recognition, Face- and Eye Tracking, Lipreading, and Sound Source Localization. Connectionist and hybrid techniques are used throughout.

Introduction

Recent developments in the computer and communication industries are rapidly increasing the amount and variety of nformation available to a wide and diverse audience. The ti-media nature of this data explosion, heral ded by the pt of the "Information Superhighway", offers i mages, text, etc. as the output presented to the informasumer. This is in stark contrast to the impoverof input options which are still largely limited to ard and mouse. Attempts at the use of alternate ave mostly focused on single alternatives and ited acceptance. to improve this situation, we have begun to process a multiplicity of signals that are carry meaning in human communication. Understanding, Witten Character-Lipreading, Face-Tracking, Eyeocalization. In combination, rmation are known to prol information for effechey allow for greater lundant information ty and freedom to n channel. Such ul in humanıg, speech such as ery

h-1 recognition⁷ and is preferred to a static, bitmapped representation of gesture's shape. The coordinates are normalized and resampled at regular intervals to eliminate differences in size and drawing speed; from these resampled coordinates

we extract local geometric information at each point, such as the direction of pen movement and the curvature of the jectory.

Tach coordinate is represented in the classifying TDNby such low-level features. Their temporal sequence cons the input layer. Ten units in the first hidden layer patterns from the input, eight units in the second aver spot patterns typical of a given gesture. Out-(one per gesture) integrate over time the evidence rresponding unit in the second hidden layer. The th the highest activation level determines the The network is trained on a set of manually es using a modified backpropagation al gong data of 80 samples/gesture, we have ependent recognition rate of 98.8% on

also incorporates a method for acs "on the fly", i.e., while the system is in tion entrop occurs, the system queries that no with and creates new templateat project onto the output units. If ris similar to the template used ris similar to the acoust a used the forea of the scale of the second to the forea of the second of the second to the state of the second of the second systems' performance is, egradation of the acousral to try to supplement wfotinagionon a touch lamas careanthi fing 'butheal so forf notepade computatisve alumut options nagleipof apppelaine otismpor hovinnf or signified above. ed**er e t**li srésaudatian bletad ĭðke or

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e a system of **network**. Kalkepsnettwoorkk of ontslied open-shape of the objects in proand enhanceducing the and out the network of ontal do in *rtual camera*, indicating the individual region is a translop a school do ingtt like face. Appropriate commands ing to catory these HK darmad such mass and is severe of the face noves out of tc. a Qurth defined rail and, in the commune of the physical camera. Figemar hous hous no school by a school do in the area classified

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Two neural networks are used for centering and size estimation respectively. They were trained by backpropagation on 5000 artificially scaled and shifted example i mages generated with a database containing 72 images of 24 faces of different sex, age, hair style, skin color, etc. Performance was evaluated on test sequences of over 2000 images of 7 persons (with different skin types) performing arbitrary movements in front of different backgrounds. Depending on the sequence, the face was located in 96% to 100% of all images in the sequence. The average difference of the actual position of the face and the output of the systemwere less than 10% of the size of the head.

Eye Tracking

The goal of gaze tracking is to determine where a person is looking from the appearance of his eye. Two potential es of a gaze tracker are as an alternative to the mouse an input modality and as an analysis tool for human-er interaction studies. The direction of eye fixation be used to determine the user's focus of attention in ndal interface; for instance, knowing whether the king at the screen or somewhere else while talking rtant in deciding whether automated speech d be activated. lon we have developed a neural - networkgaze tracker based on camera input lvanced gaze tracking, the user is ny special equipment, nor to keep ne system.comes from a camera monitor. An infrared light on on the eye. The gaze relative positions of The systemextracts on. The gray-scale put to a neural

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cribed earlier picks its target as the svicinity. It, therefore, encounters probting to track a moving talker in realis-