Multitouch Gesture Learning and Recognition System

Sashikanth Damaraju, Andruid Kerne
Interface Ecology Lab at Texas A&M University
{damaraju, andruid}@cs.tamu.edu

Abstract

We build a system that learns and recognizes multitouch gestures – movements of human fingers on a multitouch surface. We form an example vocabulary of gestures that demonstrates the subtleties of finger movements that can be recognized. A video processing system extracts a feature set representing these movements. We recognize the spatial arrangement of fingers in a gesture to address issues regarding the preprocessing of the feature set for consistency across samples of a gesture. Hidden Markov Models (HMMs) are then used to learn gestures by example, and then consistently recognize them. We present an evaluation that demonstrates the robustness of the methodology.

1. Introduction

Multitouch screens enable capture of movements of multiple human fingers on an interactive surface. Recent developments facilitate access to the required multitouch hardware, bringing the potential for supporting new forms of human-centered experience, this potential is as yet hardly realized. Our contribution is a system that understands human expressions of intent by learning and recognizing gestures performed on a multitouch surface.

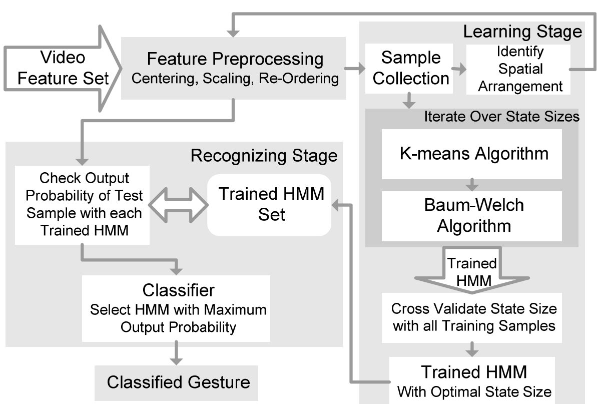

Figure 1. Multitouch Gesture Learning and Recognition Pipeline. Identification of spatial arrangement in the learning phase feeds back to feature pre-processing.

Researchers have investigated multitouch interaction for decades [1]. Multitouch gestures have generally been limited to coarse movements such as the 'wipe' and 'pile-n-browse' techniques [7], simple primitives such as 'flicks' [5] or fixed combinations of 'chords' [6]. We present a technique that learns and recognizes sophisticated hand gestures on a multitouch surface, providing end-user customizability. Our long term objective is to give human participants an interactive experience in which embodied gestures performed by the human hand are mapped to actions in ways that are natural, meaningful and intuitive.

2. Learning and Recognition Pipeline

Computationally, we define a *gesture* as a human action that begins with placing one or more fingers on the interactive surface, and ends when no fingers remain on the surface. A sequence of frames from a camera is captured to record each gesture. For each frame of the sequence, a feature set is derived by an open source video processing and feature acquisition toolkit [3], and used to recognize the gesture through a pipeline of processing stages. Figure 1 shows the stages involved in the learning and recognition pipeline.

2.1. Training Set

Our goal is to build a practical system that uses natural movements of the hand to perform complex actions within an application. To start, we developed a vocabulary of 40 different gestures for testing the current learning and recognition system (Figure 2). The gestures were formed to exemplify subtle differences in initial positions of the fingers and directions of movement. They are grouped by the number of fingers used to perform each one. Twenty samples of each gesture were collected from each of 10 users, 9 male and 1 female, all of whom are right-handed. We expect that the ability to recognize a vocabulary of gestures with subtle variations, such as the direction of

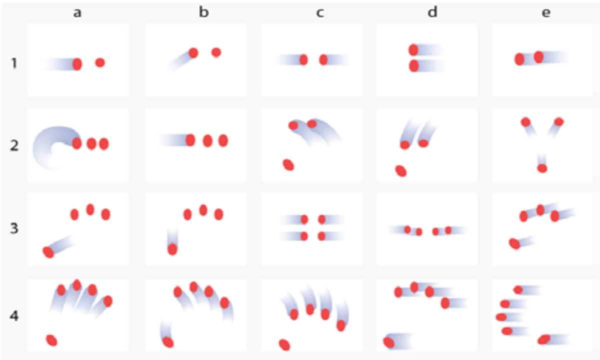

Figure 2. Vocabulary of gestures demonstrating the subtleties that can be recognized. The starting positions of the fingers are shown in red, the blue trails shows the path during the gesture.

movement of the thumb in gestures 3a and 3b, will be critical for developing expressive applications.

2.2. Feature Preprocessing

The feature preprocessing stage normalizes the data in the X, Y feature space to allow the gesture to be recognized irrespective of where it was performed on the screen. The samples of the training set are also scaled to a constant size for improved recognition.

The ordering of the fingers in the feature set provided by video processing is determined by the temporal order of placement of the fingers on the surface in the first frame of a gesture. Without preprocessing, this ordering is inconsistent across different samples of the same gesture, which is a problem for the learning and recognition system. We develop a solution to this problem of consistent feature ordering, which identifies the spatial arrangement of fingers as horizontal, vertical, or radial. The spatial arrangement is identified for the first frame of each gesture during the learning stage, and then applied during preprocessing during subsequent frames (see feedback line at the top of Figure 1).

2.3. Learning Stage

To learn gestures, we have randomly selected 20 samples of each gesture from across all users. The remaining samples are used to determine the accuracy of classification of the recognition system. During the learning phase, after the observations have been collected and preprocessed, they are passed to a K-means clustering algorithm. The K-means clustering efficiently forms an initial estimate of the HMM parameters. The estimate is, in turn, passed to the Baum-Welch algorithm, which tunes these parameters to return a high probability for only the given training sample sequences.

2.4. Recognition Stage

For each sample to be recognized, we pass the sample into each trained HMM. The probabilities output from each HMM are collected and compared. We label the sample as the multitouch gesture whose model returns the highest probability.

3. Results

A random selection of 20 training samples for each gesture from the entire set of all 10 users is used to train HMMs, and the remaining samples used to determine the overall classification rate of the system. The classification rates for the gestures using two, three, four and five fingers are 93.8%, 91.4%, 92.1% and 88.8%, for an average gesture recognition rate of 91.5%, and the result is statistically significant ($p < .0001$). These results show that our technique classifies gestures within a reasonable accuracy for practical use. As the HMM can be trained using samples from more than one user, it can also be stored within an application or shared across users to avoid re-training.

Future work will define intuitive gesture vocabularies for use with the combinFormation mixed-initiative information composition platform [2], and apply the present gesture learning and recognition methods to develop an expressive multitouch information composition system.

4. References

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