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Hand gestures recognition classification

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Abstract

The use of hand gestures for human-machine interaction offers an enticing alternative to bulky interface devices. The current study discusses the classification of gestures in real time and aims to create an algorithm capable of classifying gestural control commands accurately. For the classification of a gesture vocabulary of eight dynamic hand gestures, two separate classifiers were created. The established classifiers were: K-means + rule-based classifier and classifier of to test the accuracy of classification recognition in which a test set of 180 trajectories was categorized, an experiment was conducted. The accuracies obtained for the K-means and Learning classifier systems(LCS) classifiers, respectively, are 90 and 94 percent.

Keywords: Component: Classification; Human machine interface; LCS; K-means; Gesture recognotion

1. Introduction

An important part of human communication is the act of gesturing, which is used to communicate a variety of commands, emotions and thoughts. Research on hand gesture recognition has gained interest because it offers an enticing alternative for human-machine interaction to bulky interface devices. Smart home interfaces provide potential application areas for control based on gesture recognition. [1] [2], computer interfaces [3] [4], medicine [5] and robotics [6]. In dynamic hand gesture recognition systems (GRS) In order to produce a trajectory that reflects the hand's motion, the hand must first be tracked by a tracking algorithm. Then this trajectory serves as feedback to the classifier of gestures. Classification in a GRS is a stage in which the monitored trajectory is classified (recognized) as a single gesture or as a non-gesture (random hand movement) of a predefined gesture vocabulary. For the classification of gestures, several methods were used, including: Neural Networks, Fuzzy C means inference systems [7], Hidden Markov Models [8], Support Vector Machines [9], etc. While most of the methods mentioned demonstrate high precision, the accuracy of the results depends on the presence of a large amount of training data. This can limit their implementation and rule out choices, such as gestures that are self-defined. Furthermore, calculation times are long for certain algorithms, except real-time operation. A preliminary stage of gesture spotting involves certain classifiers to detect track segments that may contain gestures, and these segments are then sent to the classifier.

A popular GRS architecture is described in Figure 1 [10]. The state machine is an application which is controlled by the recognized gestures.

In this paper, we compare two classifiers of gesture recognition built to recognize a gesture vocabulary of six complex gestures, a classifier of the longest common substring (LCS) and a classifier of k-means based on rule [11]. The gesture vocabulary recognized by the classifiers and a brief overview of the classifiers are defined in Section II. The experimental procedure and data analysis are mentioned in section III and the results of the classifier precision experiment are given in section IV.

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2. Methods

2.1 Gesture vocabulery

Six complex gestures form the gesture language (Figure 2). After a preliminary user experiment, the vocabulary was built and the selected movements were chosen using the criterion of: intuitive, memorable and distinct enough to prevent misunderstanding between them. In the gesture vocabulary, two classes are defined: navigation (up, down, left and right) and control (cancel and choose). The period is about 1 second for navigation gestures and about 2 seconds for control gestures.

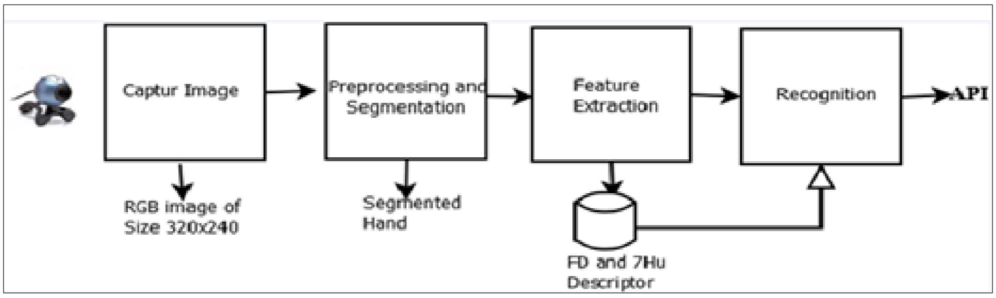

Figure 1 Basic architecture for complete gesture recognition

In gesture recognition, one of the key challenges is deciding where the gesture starts and ends. In order to detect the absence of hand movement and to mark the beginning and end of a gesture, one way to overcome this problem is to pause before and after a gesture. The experiment was carried out in this paper using pauses between gestures.

2.2 Classifiers tested

Two classifiers were introduced; a base classifier of the k-means law, and a classifier of the LCS [11]. Large training datasets are not needed for both, and their computational load is low. The LCS classifier's computational load is a bit higher, but it does not require a spotter, whereas one is needed by the K-means rules-based classifier.

K-means Rule based classifier – There are two steps to the classifier. The first is based on a training set of gestures clustering, using two characteristics: aspect ratio and standard deviation of distances from the boundary of the trajectory to its center of gravity. The movements are split into two pieces.

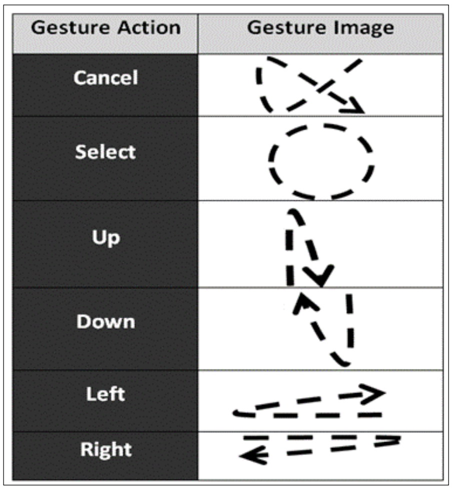

Figure 2 Gesture vocabulary for GRS remote control

Groups: control and navigation. The clustering stage is followed by a rule-based stage, where specific gestures are recognized using a sequence of rule filters [11]

- Classifier Longest Common Subsequence (LCS)-The LCS approach is based on complex principles of programming. Absolute angels of the series of motion vectors in a trajectory are the function used by the LCS classifier. The angle series is compared by the algorithm to pre-defined template patterns that represent the six movements that seek the highest correlation. Due to popular user variations and alternative starting points [11], some gestures are represented by multiple models. Due to low precision in recognizing the 'cancel' gesture by the k-means classifier, this classifier was created.

3. Experiment

3.1 Subjects and experimental procedure

The experiment was conducted to determine the accuracy rate of the classifier. In the gesture language, four well-behaved consumers performed all six movements. There were thirty trajectory samples reported per gesture. In addition, thirty non-gesture trajectory samples were evaluated for a total of 180 gesture trajectories to determine the ability of the classifiers to reject spontaneous hand gestures. Using a magnetic position sensor from Fastrak (Polhemus), the users' hand positions were monitored for four seconds. In order to obtain very precise ground truth trajectories, a location sensor was used rather than a vision-based tracker. Test trajectories used by both classifiers are shown as inputs in figure 3.

3.2 Data analysis

The output of the classifier was summarized in a matrix of uncertainty. Four measurements are representative of the performance of the classifier:

Accuracy rate (hit) means True positive rate (TPR):-percentage of correctly identified trajectory samples from all tested trajectory samples.

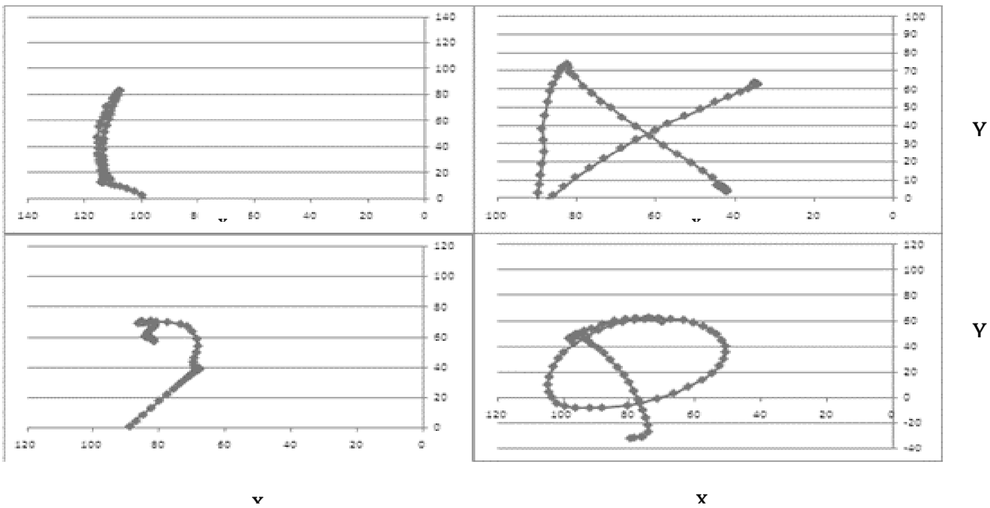

Figure 3 Sample trajectories of: a. up, b. cancel, c. non-gesture, d. select

Table 1 Testing classifiers experiment measurements

Measurements	LCS Classifier	K-means +Rule based Classifier
Accuracy Rate	94%	90%
Error Rate	6%	10%
False Alarm	16%	16%
Correct Rejection	84%	84%

Error rate (miss) means false negative rate (FNR) :-the proportion of trajectory samples incorrectly categorized from all tested trajectory samples.

False alarm: the percentage of non-gesture trajectories classified from all non-gesture trajectory samples evaluated as control gestures.Correct rejection – percentage of non-gesture classified as non-gestures from all non-gesture trajectory samples tested Clearly a better classifier has a high accuracy rate, correct rejection, low error rate and false alarm.

4. Results and discussion

The LCS classifier (Table 1, Figure 4) achieved high accuracy (mean number) and low error (mean number) rate. However some of the recognition rates required further investigation in order to achieve future improvements:

- Up gesture-Findings suggest that the up gesture has the lowest rate of "HIT" (84%) and the highest rate of "MISS" (16%). The miss-classified up gestures are known as down gestures by Al. Further research found that the majority of miss-classified samples were the result of users making a slight down motion before the main up motion. Since the users were seasoned users, the algorithm must be strengthened by further analysis of the actions of the users to enhance the classifier. The results can be improved by adding an additional pattern that reflects the motion mentioned above..
- Down gesture, while the accuracy rate is high, 7% of misclassified gestures were found to be the result of identifying the motion as an up gesture. This is because prior to beginning the down motion of the gesture, users pushed their hand up. A potential solution to the issue is to introduce a delay at the beginning of each gesture in order to detect the beginning of the true gesture. A different approach is possible, which consists of introducing the motion as part of the down gesture up to the beginning of the gesture and thereby adding an extra sequence.

Table 2 The confusion matrix of the Proposal system

LCS Classifier							
	Cancel	Select	Up	Down	Left	Right	Non-Gesture
Cancel	93%	0%	7%	0%	0%	0%	0%
Select	0%	97%	0%	0%	0%	3%	0%
Up	0%	0%	84%	16%	0%	0%	0%
Down	0%	0%	7%	93%	0%	0%	0%
Left	0%	0%	0%	0%	100%	0%	0%
Right	0%	0%	0%	0%	3%	97%	0%
Non-Gesture	0%	0%	3%	10%	3%	0%	84%

K-means + Rule-Based Classifier							
	Cancel	Select	Up	Down	Left	Right	Non-Gesture
Cancel	70%	7%	0%	0%	0%	0%	23%
Select	0%	100%	0%	0%	0%	0%	0%
Up	0%	0%	97%	0%	0%	0%	3%
Down	0%	0%	0%	90%	0%	0%	10%
Left	3%	0%	0%	0%	83%	0%	13%
Right	0%	0%	0%	0%	0%	100%	0%
Non-Gesture	0%	13%	3%	0%	0%	0%	84%

- A good precision (number) was achieved by the K-means + Rule-Based classifier, but its results were lower than those of the LCS classifier. Below is a discussion of the factors influencing misclassified gestures.
- Cancel gesture-Findings show that the lowest "HIT" rate (70 percent) is found in the cancel gesture. One of the reasons for creating a second classifier was the low detection of the cancelation gesture. Further analysis of the miss-classified cancel gestures shows that the main explanation stems from the "harsh" conditions of the rules

that differentiate the cancel gesture from spontaneous hand movements, such as: requiring a single intersection within the trajectory of the gesture and requiring the end and beginning of the gesture to be on the same side of the bounding box of the trajectory, etc. Optimizing the rule threshold parameter values is a potential way of fixing this problem.

- Left gesture: the analysis of the research collection reviles that a curved left gesture is executed by some of the users. This motion should be considered in future research and because the rules for a horizontal navigation gesture in the k-means classifier require a broad standard deviation of the distances from the center of gravity of the gesture to the boundary of the trajectory and a small aspect ratio, two requirements that do not exist.The LCS classifier proved superior to the classifier based on the K-means law. However, analyzing the confusion matrices, we can see that different classifiers provided better results for different gestures. Growing both classifiers can therefore enhance recognition.

5. Conclusion

This paper discusses the classification stage of a GRS developed for remote control of a TV channel selection interface. The paper presents the comparative experiment of the two types of candidate classifiers: a k-mean rule based classifier and a LCS classifier. The experimental results prove the superiority of the LCS classifier. The experiment identified deficiencies in both classifiers, and provides directions for further improvements.

Compliance with ethical standards

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Disclosure of conflict of interest

All authors declare that they have no conflicts of interest.

References

[1] T Baudel and M. Baudouin-Lafon, Charade: remote control of objects using free-hand gestures. Comm. ACM. 1993; 36(7): 28–35.

[2] Yoon HS, Soh J, Bae YJ, Seung Yang H. Hand gesture recognition using combined features of location, angle and velocity. Pattern Recognition. 2001; 34(7): 1491-1501.

[3] Kang H, Woo Lee C, Jung K. Recognition-based gesture spotting in video games. Pattern Recognition Letters. 2004; 25(15): 1701-1714.

[4] Geer D. Will gesture-recognition technology point the way? Computer. 2004; 37(10): 20-23.

[5] Wachs J, Stern H, Edan Y, Gillam M, Feied C, Smith M, et al. Gestix: A doctor-computer sterile gesture interface for dynamic environments. Soft Computing in Industrial Applications: Recent and Emerging Methods and Techniques. 2007; 30–39.

[6] Baudel T, Beaudouin-Lafon M. Charade: Remote control of objects using free-hand gestures. Communications of the ACM. 1993; 36(7): 28-35.

[7] Freeman WT, Weissman C. Television control by hand gestures. Paper presented at the Proc. of Intl. Workshop on Automatic Face and Gesture Recognition. 2000; 179-183.

[8] H Stern, D Frolova, S Berman. Hand Gesture Recognition for TV Remote Control using Tree-Based Ensemble and LCS Classifiers, WORLDCOMP'10 The 2010 World Congress in Computer Science, Computer Engineering, and Applied Computing, July 12-15, Las Vegas, USA. 2010.

[9] Starner TE. Visual Recognition of American Sign Language using Hidden Markov Models. 1995.

[10] Vapnik V. Statistical Learning Theory. John Wiley and Sons, New York, 1998.

[11] Yu J. General c-means clustering model. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2005.

[12] Manigandan M, I Manju Jackin. Wireless Vision Based Mobile Robot Control Using Hand Gesture Recognition through Perceptual Color Space ace, International Conference on Advances in Computer Engineering 2010; 95-99.