

Hand Motion Recognition via Fuzzy Active Curve Axis Gaussian Mixture Models: A Comparative Study

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Abstract—Unconstrained human hand motions consisting grasp motion and in-hand manipulation lead to a fundamental challenge that many algorithms have to face in both theoretical and practical development, mainly due to the complexity and dexterity of the human hand. In this paper, fuzzy active curve axis Gaussian Mixture Model (FAcGMM) is proposed by introducing a weighting exponent on the fuzzy membership into active curve axis Gaussian Mixture Models (AcaGMM) to improve its convergence efficiency, and then FAcGMM is used to recognize human hand motions. In addition, a comparative study of recognition methods including FAcGMM, Time Clustering (TC), Empirical Copula (EC), GMM and HMM is presented to recognize human hand motions including both grasps and in-hand manipulations from different subjects with varying training samples.

Keywords—Motion Recognition; Gaussian Mixture Models; Active Curve Axis Gaussian Mixture Models; Fuzzy Active Curve Axis Gaussian Mixture Models

I. INTRODUCTION

Human-robot skill transfer is of great importance in order to develop advanced multifingered manipulation planning and control systems. Learning from human hand motions is preferred for human-robot skill transfer in that, unlike teleoperation-related methods, it provides non-contact skill transfer from human motions to robot motions by a paradigm that can endow artifacts with the ability for skill growth and life-long adaptation without detailed programming [1].

During the learning process, hand motion recognition is still an open problem due to the complexity and dexterity of the human hand, though it had been investigated in the past two decades. The attractiveness of applying neural network could be due to the nonlinearity of the network. Neural network approaches demonstrated its powerful grasp recognition in Glove-Talk project [2], [3]. Sato et al. [4] identified predetermined gestures in a fast and robust manner by using a neural network which has been properly trained beforehand. Support vector machine (SVM) was employed by Zoellner et al [5] to classify dynamic grasps in the framework of Programming by Demonstration. In addition, David et al. [6] used a combination of discriminative (SVM, conditional random fields) and generative approaches, Hidden Markov Model (HMMs),

for the modeling and recognition of actions through motor primitives. However, the choice of the SVM kernel function has a significant effect on its performance and the best choice is application dependent. Natal et al [7] and Bedregal et al [8] developed fuzzy rule-based methods for the recognition of hand gestures, however the methods are highly dependent on a detailed previous analysis of the recognized gesture features with manual transfer involved. Note that Heumer et al [9] attempted to provide a performance criteria for hand grasp classification including 28 algorithms provided by Weka data mining software package. However these algorithms usually require more parameters such as finger angular speed instead of position trajectories only, they have also paid less attention to the context of intelligent robotics, for instance, real-time recognition requirement.

In addition, state of the art in human hand motion recognition can be represented by Gaussian Mixture Model (GMMs), HMM and their variants, since they are very rich in mathematical structure and hence their theoretical basis can be adopted for a wide range of applications. Calinon and Billard [10] proposed an approach to teach incrementally human gestures to a humanoid robot, which consists of projecting the movement data in a latent space and encoding the resulting signals in a GMM. Kaustubh et al. [11] used GMMs to classify one-handed gestures based on ultrasonic sensors, and the experiment showed simplified one-handed gestures can be recognized with a high accuracy. On the other hand, in [12], the moving hand is tracked and analyzed by Fourier descriptor (FD) from image sequences, and then the feature vector consisting the spatial and temporal features is processed by HMMs for recognition of the hand gesture. Bernardin et al. [13] presented a method using HMMs to recognize continuously executed sequences of grasping gestures. Both finger-joint angles and information about contact surfaces, captured by a data glove and tactile sensors, are used. By using the Kamakura taxonomy, most of all grasps used by humans in everyday life can be classified, increasing the system's application domain to general manipulation tasks. For 12 grasp classes, and with very little training data, a recognition accuracy of up to 89% for a single-user

system and 95% for a multiple-user system could be reached. Ju *et al* [14] compared Time Clustering (TC) with HMMs and GMMs on the recognition rate of 13 types of different grasps. Just *et al.* [15] provided an empirical comparison of two state-of-the-art techniques, HMMs and Input/Output HMMs, for temporal event modeling combined with specific features on two different datasets.

Gaussian Model is confined to normal distributed clusters, so that more Gaussian components are needed for approximating the data with curve manifolds[16], [17]. In order to solve this problem, Active curve axis Gaussian Model (AcaGM), proposed by Baibo[18], is a new non-linear probability model imagined as Gaussian Model being bent at the first principal axis. Inspired from the mechanism of Fuzzy C-means (FCM) [19], in this paper, we firstly introduce a weighting exponent on the fuzzy membership into active curve axis Gaussian Mixture Model (AcaGMM) in order to improve the efficiency of convergence and then use the proposed fuzzy active curve axis Gaussian Mixture Model (FAcaGMM) to recognize the human hand motions. In addition, a comparative study of recognition methods including FAcaGMM, Time Clustering (TC), Empirical Copula (EC), GMM and HMM is presented. This paper is organized as follows: Section II revisits the mechanism of AcaGMM. Section III proposes the FAcaGMM with an improved convergence speed. Section IV proposes the algorithm to recognize hand motions using FAcaGMM. The comparative experiments are presented in section V. Finally the paper is concluded with remarks and future work.

II. ACTIVE CURVE AXIS GAUSSIAN MODEL

Let $\mathcal{X} = \{x_1, \dots, x_n\}$ be a d -dimensional observed dataset of n vectors. The distribution of $\mathcal{X}$ is based on one Gaussian or bent Gaussian. First, the samples are mapped to the coordinate system determined by PCA:

$$y_i = Q \times (x_i - T) \quad (1)$$

where T and Q denote the translation vector and rotation matrix of PCA individually. Let $\mathcal{Y} = \{y_1, \dots, y_n\}$ be the transferred coordinates of $\mathcal{X}$ by PCA. The d dimensions of $\mathcal{Y}$ are then denoted as $v = [v_1, \dots, v_d]^T$.

Then least-squares fitting method [20] is used to fit the coordinates $[v_1, v_2]^T$, which are in $\mathcal{Y}$'s principal plane, with the standard curve which is defined as

$$y = ax^2 + b \quad (2)$$

The quadratic term coefficient a indicates the bend degree of the curve. The bigger a is, the more the principal axis bends. b is the offset of the curve. The principal axis is bent to be $y = ax^2 + b$ and the Gaussian model with the bent axis is AcaGM. An example of AcaGM is given on the left of Fig. 1.

The projective points of one sample can be thought as the points on the principal axis who have the local minimal distances with the sample. The distances between sample and points along the principal axis have zero derivatives at the sample's projective points. Given any sample $[v_{1t}, v_{2t}]^T$ which

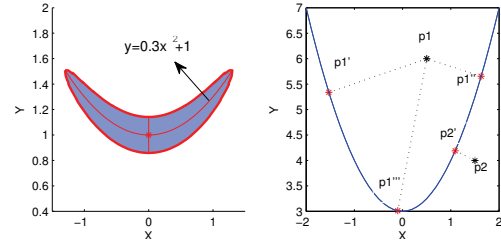


Fig. 1. AcaGM(left) and projection points on the principal curve axis(right).

is the transferred coordinates from x_t , its distance to a point $z = [z_1, z_2]^T$ on the standard curve satisfies

$$d^2 = (v_{1t} - z_1)^2 + (v_{2t} - z_2)^2$$

Using the Lagrange method, the partial derivatives to z_1 and z_2 of $d^2 - \lambda(z_2 - az_1^2 - b)$ are equal to zero,

$$(z_1 - v_{1t}) - \lambda az_1 = 0$$

$$2(z_2 - v_{2t}) - \lambda = 0$$

Eliminate λ ,

$$z_1 - v_{1t} = 2az_1(z_2 - v_{2t}) \quad (3)$$

with the standard curve equation $z_2 = az_1^2 + b$, we can solve all the real roots of this equation, which are the projective points of sample $[v_{1t}, v_{2t}]$. In the principal plane, one point may have several projection points on the principal curve axis, because bending the principal axis may cause one point locates in several different normal directions of the curve axis as shown on the right of Fig. 1. Supposing $z = [z_1, z_2]^T$ is the j th projective point of the sample $[v_{1t}, v_{2t}]$, the arc length of z is formulated as

$$l_j(v_{1t}) = \int_{(0,b)}^{(z_{1j}, z_{2j})} \sqrt{(dz_{1j})^2 + (dz_{2j})^2}$$

z is on the standard curve, so it satisfies $z_2 = az_1^2 + b$. So we have

$$l_j(v_{1t}) = \frac{1}{2} z_{1j} \sqrt{1 + 4a^2 z_{1j}^2} + \frac{1}{4|a|} \ln \left(2|a| z_{1j} + \sqrt{1 + 4a^2 z_{1j}^2} \right) \quad (4)$$

The distance between the sample $[v_{1t}, v_{2t}]^T$ and its projective point z is

$$l_j(v_{2t}) = \sqrt{(v_{1t} - z_{1j})^2 + (v_{2t} - z_{2j})^2} \quad (5)$$

Then the probability density function of point x_t is the sum probability of its projective points:

$$p(x_t|\theta) = \sum_{j=1}^{J_t} \prod_{s=1}^2 \frac{\exp(-l_j^2(v_{st})/2\Sigma_s)}{\sqrt{2\pi|\Sigma_s|}} \prod_{s=3}^d \frac{\exp(-v_{st}^2/2\Sigma_s)}{\sqrt{2\pi|\Sigma_s|}} \quad (6)$$

Where the parameter set $\theta = (\mu, \Sigma, C, Q, T)$; C denotes the control parameters of a standard curve $f: y = ax^2 + b$; J_t is the number of the projective points of sample x_t .

III. FUZZY ACTIVE CURVE AXIS GAUSSIAN MIXTURE MODELS

For a faster convergence speed of AcaGMMs, based on the dissimilarity function in Fuzzy C-means [21], a dissimilarity function for FAcGMMs is defined as:

$$d_{it}^2 = \frac{1}{\alpha_i p_i(x_t|\theta_i)} \quad (7)$$

where α_i is the weight of i th component; $p_i(x_t|\theta_i)$ is from equation 6,

Compared to the standard dissimilarity function in Fuzzy C-means, the dissimilarity function defined by equation 7 consists of not only the distance but also the covariance and mixture weights, and it is in direct ratio with the exponent of the distance. The objective function is extended from Fuzzy C-means objective function as:

$$J_m(U, \mathcal{X}, \mu, \Sigma) = \sum_{t=1}^n \sum_{i=1}^k (u_{it}^m d_{it}^2) \quad (8)$$

Minimizing J_m is performed by the same u_{it} operations of FCM using

$$u_{it} = \left[\sum_{j=1}^k \left(\frac{d_{it}}{d_{jt}} \right)^{\frac{2}{m-1}} \right]^{-1} \quad (9)$$

The new mixture weights are estimated by:

$$\alpha_i^{new} = \frac{\sum_{t=1}^n u_{it}^m}{\sum_{i=1}^k \sum_{t=1}^n u_{it}^m} \quad (10)$$

The parameters of curve axis (a_i, b_i) in C_i can be achieved by

$$(C_i^{new}, T_i^{new}, Q_i^{new}) = LSFM(PCA(\mathcal{X}'_i)) \quad (11)$$

where

$$\mathcal{X}'_i = [w_{i1}, \dots, w_{in}] \cdot [x_1, \dots, x_n] \quad (12)$$

$PCA()$ is principal component analysis function for estimating the translation matrix T_i^{new} and rotation matrix U_i^{new} . $LSFM()$ is least-squares fitting method for estimating control parameters $C_i^{new} = (a, c)$ which shapes the curve axis with standard curve $y = ax^2 + b$; The centers and covariances can be computed through equations 13-15.

$$\begin{aligned} \mu_i^{new} &= (Q_i^{new})^{-1} \underbrace{[0, b, 0, \dots, 0]^T}_d + T_i^{new} \\ &= (Q_i^{new})^{-1} \underbrace{[0, b, 0, \dots, 0]^T}_d + \frac{\sum_{t=1}^n u_{it}^m x_t}{\sum_{t=1}^n u_{it}^m} \end{aligned} \quad (13)$$

$$\Sigma_{ie}^{new} = \frac{\sum_{t=1}^n u_{it}^m \bar{L}_{te}^{(i)}}{\sum_{t=1}^n u_{it}^m} \quad (e = 1, 2) \quad (14)$$

$$\Sigma_{i(3-d)}^{new} = \frac{\sum_{t=1}^n u_{it}^m (x_t - \mu_i^{new})_{(3-d)} (x_t - \mu_i^{new})_{(3-d)}^T}{\sum_{t=1}^n u_{it}^m} \quad (15)$$

Where $\Sigma_{i(3-d)}$ is the covariance in the $d-3$ dimension space orthogonal to the principal plane.

With new centers and covariances, the log-likelihood expression is given by:

$$\begin{aligned} \log(\mathcal{L}(\Theta|\mathcal{X})) &= \log \left(\prod_{t=1}^n p(x_t|\Theta) \right) \\ &= \sum_{t=1}^n \log \left(\sum_{i=1}^k \alpha_i p_i(x_t|\theta_i) \right) \end{aligned} \quad (16)$$

where $p_i(x_t|\theta_i)$ is from equation 6.

The EM algorithm of FAcGMMs is provided in algorithm 1 where d_{it} is obtained from equation 7.

Algorithm 1 EM algorithm of FAcGMMs.

Require: Fix k, m and ε { k is the number of components $2 < k < n$; m is the degree of fuzziness $m > 1$; ε is a small preset real positive number}.

- 1: $U \leftarrow fcm(data, k)$ {Use FCM to generate matrix U satisfying equation 9}
- 2: **repeat**
- 3: **for all** i such that $1 \leq i \leq k$ **do**
- 4: $\alpha_i^{new} \leftarrow equation10$ {Compute the k fuzzy mixture weights α_i^{new} using equation 10}
- 5: $a_i \leftarrow equation11$
- 6: $\{C_i^{new}, T_i^{new}, Q_i^{new}\} \leftarrow equation11$ {Compute the k fuzzy control parameters of standard curve, translation and rotation matrices using equation 11 }
- 7: $\mu_i^{new} \leftarrow equation13$ {Compute the k fuzzy centers using equation 13}
- 8: $\Sigma_i^{new} \leftarrow equations14-15$ {Compute the k fuzzy covariance matrices using equations 14-15 }
- 9: **end for**
- 10: $U^{new} \leftarrow equation9$ {Upgrade the fuzzy membership using equation 9 }
- 11: $\log(\mathcal{L}(\Theta|\mathcal{X}))^{new} \leftarrow equation16$ {Compute the log-likelihood using equation 16}
- 12: **until** $\frac{\log(\mathcal{L}(\Theta|\mathcal{X}))^{new}}{\log(\mathcal{L}(\Theta|\mathcal{X}))^{old}} - 1 \leq threshold$ {Stop if the relative difference of the log-likelihood between two adjacent iterations is blow the preset threshold}

An example of the comparison of AcaGMMs with fuzzy AcaGMMs in terms of the convergence speed could be seen in Fig. 2, where the overall fitnesses of these two methods are almost similar while fuzzy AcaGMMs need much less iterations. For more details about the convergence comparisons, please refer to our previous papers [22], [19].

IV. RECOGNITION VIA FACAGMM

The algorithm of equation 17 and equation 18 is constructed to recognize the testing motions. Supposing there are a attributes in the human hand motion dataset. The dissimilarity

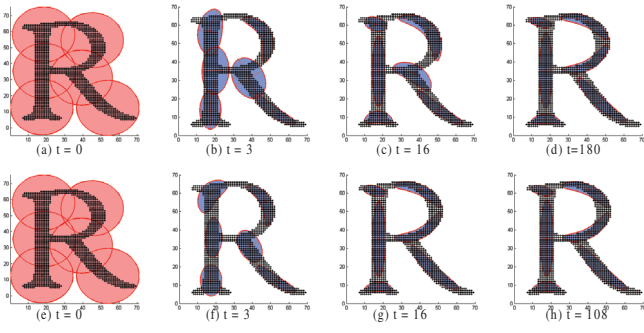


Fig. 2. A comparison of Convergence processes of AcaGMM (first row) and FAcaGMM (second row). t is the number of iterations

of the testing motion and the trained model of FAcaGMM is defined as

$$Dis = \frac{1}{a} \sum_{k=1}^a AvgDis^{(k)} \quad (17)$$

where k is the number of the attributes; $AvgDis^{(k)}$ is the average distance of the k^{th} attribute and is calculated by

$$AvgDis^{(k)} = \frac{1}{Cnum^{(k)}} \sum_{i=1}^{Cnum^{(k)}} |(Tmotion^{(k)}(t_i) - Center^{(k)}(i))| \quad (18)$$

where $Cnum$ is the number of the Gaussian components which is set before applying EM algorithm; $i = 1, \dots, Cnum$ is the index of the Gaussian components; t_i is the time pint of i^{th} Gaussian component; $Tmotion(t_i)$ is the angle value or finger tip position of the testing hand motion at t_i ; $Center(i)$ is the i^{th} model center. The corresponding motion points at the time t_i are identified according to the time points of the model centers, and then the average distances between the centers and these points which are in the same time as these FAcaGMM's centers along the dash line are calculated, as shown in the Fig 3. It calculates the average distance between testing motions and FAcaGMM centers. The testing sample is recognized as the corresponding grasp class with the minimum dissimilarity.

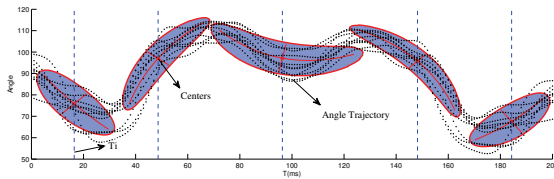


Fig. 3. An example of FAcaGMMs based in-hand manipulation motion recognition

V. EXPERIMENT

In order to evaluate the proposed algorithms, a comparative study is constructed by comparing FAcaGMM with TC, EC, GMM and HMM [14], [23]. TC is a fuzzy time-modeling approach based on fuzzy clustering and Takagi-Sugeno modeling with numerical value as output, and its details can be seen

in our previous paper [14]. EC was introduced to recognize human hand motions for the first time using the proposed motion template and matching algorithm in [23]. The experiments are implemented under two scenarios a) training with various samples from single subject; b) training with various samples from multiple subjects. In this study, two datasets, 13 grasps and 10 in-hand manipulations, are employed.

A. Experiment Set-up

A fully instrumented data glove, CyberGlove from Immersion Corporation, has been employed to measure the finger joint angles during the hand movement. It can accurately transform hand and finger motions into real-time digital joint angle data by proprietary resistive bend-sensing technology. The sampling frequency of CyberGlove system in our experiments was set to 100Hz without any filter. The joint angles are measured by 22 bend sensors, which include three flexion sensors per finger, four abduction sensors, a palm-arch sensor, and sensors to measure flexion and abduction. Each sensor is extremely thin and flexible and is virtually undetectable in the lightweight elastic glove. CyberGlove is calibrated through the software from the company, and displayed by VirtualHand Studio software which converts the data into a graphical hand mirroring the subtle movements of the physical hand.

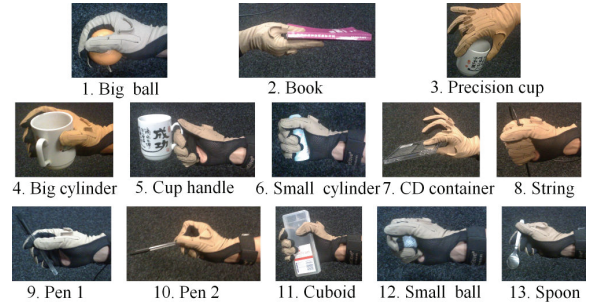


Fig. 4. Selected grasping tasks

Six (2 female, 4 male) healthy right-handed subjects volunteered for the study, their ages range from 23 to 35 with the average is 29.5 years. All subjects were trained to manipulate different objects, each grasp or in-hand manipulation is repeated 20 times for every subject. Both grasps and in-hand manipulation are considered in the study of object manipulation.

1) *Grasp*: According to the human hand grasp taxonomy [24], hand grasps are classified into 6 atomic different types, for instance, power grasps, precision grasps, and circular/prismatic grasps, etc. We selected 13 different grasp gestures as shown in Fig. 4 to test the algorithm recognition ability. Cup has been selected three times respectively in motions 3, 4 and 5 with different strategies. In motion 3, only three fingers are used to precisely contact the cup top; in motion 4, five fingers are laterally attached to the cup and cup handle is grasped with three fingers in motion 5.

2) *In-hand Manipulation*: The other dataset is for in-hand manipulation, which is much more complex than simple grasp

TABLE I
10 TYPES OF IN-HAND MANIPULATIONS

1	Open a mobile phone and then close it.
2	Screw to open a small bottle using only thumb, index finger and middle finger.
3	Pick up a coin and move it from the fingertip to the palm
4	Remove the pencil from back to front for writing, as shown in figure 5: (a) pencil walking
5	Pick up a pencil and simply rotate to write, as show in figure 5:(c) simple rotation
6	Pick up a pencil and complexly rotate to write, as show in figure 5:(d) complex rotation
7	Screw to open a big bottle using all five fingers
8	Roll a small cylinder
9	Pick up a scissor and cut paper
10	Pencil flips, as shown in figure 5:(b) pencil flips

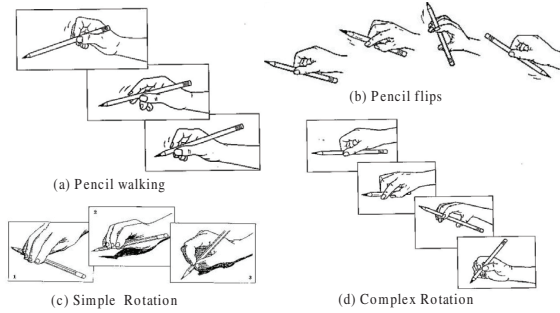


Fig. 5. Four examples of pencil in-hand manipulation

motion and associated with the most complex human motor skills. It's the ability to change the position/orientation or adjust an object within one hand. Ten types of manipulations are recorded also by Cyberglove as listed in table I, and a few examples are shown in Fig. 5.

B. Experiment 1- Training with Various Samples from Single Subject

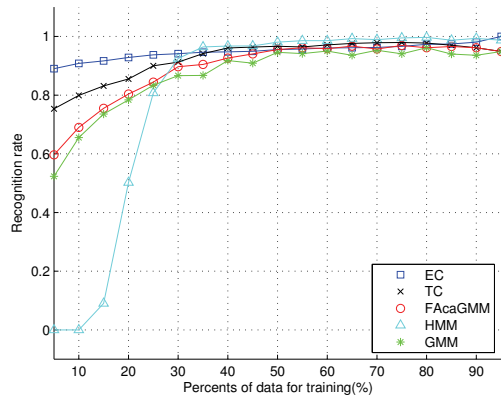


Fig. 6. Recognition results with various training percentages from single subject on grasp dataset

An empirical study was designed to evaluate sensitivity of these five methods in terms of change of the rate of training samples for the single subject. There are 13 grasp models

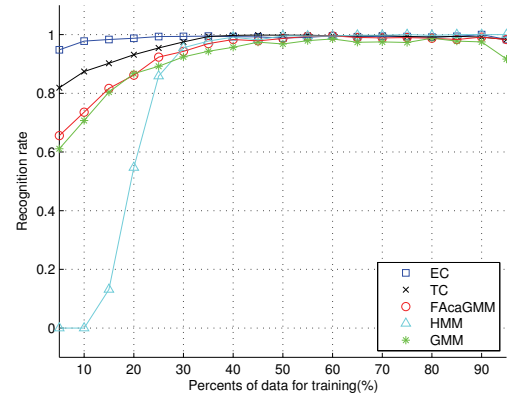


Fig. 7. Recognition results with various training percentages from single subject on in-hand manipulation dataset

and 10 in-hand manipulation models for each single subject, where each subject repeated 20 times for each motion. Each model of any subject is trained with various percentage of the data ranging from 5% to 95% from the same subject. The trained model is used to test other unused data from the same subject. The experimental results with various percentage of training data are illustrated in Fig. 6 and Fig. 7 for the two datasets. It finds that the performance of these five methods are all improved with the increase of the training datasets and their accuracies stabilize with more than 30% training data. The recognition rate of HMM improves from 0% to more than 90% when training data increase from 5 to 30 percentages and it reaches as high as that of EC with more than one third training data. Compared with GMM, FAcaGMM achieves a better result with all the various sample rates. TC stays in the middle of EC and FAcaGMM, EC presents the best overall performance among the five methods. The results demonstrate that the variation of the training samples does substantially affect performance of these methods. The increase of the training data can result in about 90, 30, 30, 20 and 10 percent increases of the recognition rates for HMM, GMM, FAcaGMM, TC, EC. It presents that HMM is sensitive to the varying training data more than any of the other four methods.

C. Experiment 2- Training with Various Samples from Multiple Subjects

Similarly an experiment was conducted to evaluate the effects of different training rates on the classifiers' performance for multiple subjects. Regarding to experiment 2, there are 13 grasp models and 10 in-hand manipulation models for all the six subjects. Each model was trained by the mixed samples from all six subjects. Each subject contributes the same amount of samples to the training data. All the other samples which are not included in the training data are used to evaluate the models trained by multiple subjects' samples. The percentage of the training data ranges from 5% to 95%

The experimental results are provided in Figs. 8 and 9 for grasp and in-hand manipulation datasets respectively. HMM

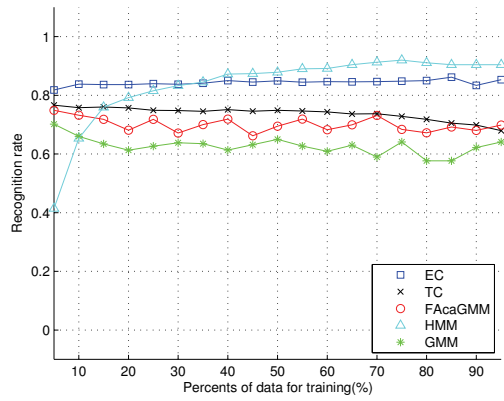


Fig. 8. Recognition results with various training percentages from multiple subjects on grasp dataset

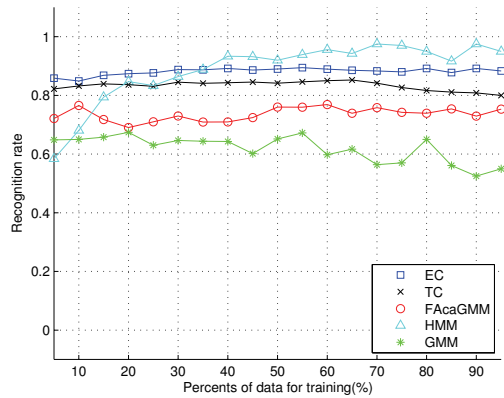


Fig. 9. Recognition results with various training percentages from multiple subjects on in-hand manipulation dataset

achieves an improvement of the recognition rate from less than 50% to 90% in terms of usage of the training samples. Different from the previous experiment results, there are no significant changes of recognition rates for the other methods with varying training samples. It is confirmed that HMM is the most sensitive method responding to varying training samples. HMM can achieve the highest accuracy with more than 40 percent training samples, but the proposed FAcaGMM, like EC and TC, outperforms HMM and GMM when the training samples are less than one fifth due to the insensitiveness to the varying percentage of the training data. FAcaGMM's performance is consistently better than GMM's thanks to the non-linear characteristic, and the Gaussian Mixture Regression (GMR) could be potentially used to generate the desired trajectory. Though TC and EC have higher recognition rate than FAcaGMM, TC is limited to the motion planning directly transferred from recognition results which are numerical values [14], and it is hard to generate desired trajectory from the dependence structure for EC [23]. FAcaGMM provides an effective solution to the applications which require abstracted patterns to store the motion features, and require an approach

to generate the desired trajectory from these features.

VI. CONCLUSIONS

In this paper, we have proposed a novel FAcaGMM with a fast convergence speed, which is used to recognize human hand motions. A comparative study covering different subjects and different training samples has been conducted to compare the methods including FAcaGMM, TC, EC, GMM and HMM. Two datasets consisting of 13 different types of grasps and 10 in-hand manipulations have been employed for the algorithm evaluation. Experiment results have demonstrated that FAcaGMM consistently outperforms GMM in terms of the recognition rate because it is a component-based modeling method having the capability of modeling datasets with curve manifolds. FAcaGMM, like TC and EC, is insensitive to the varying training samples to certain extent, which means that it has advantages over practical applications, especially when requiring a fast training model process or lacking sufficient training datasets. Its performance substantially depends on the number of Gaussian components. It utilizes abstracted patterns to store the motion features, and the desired trajectory can be generated from these features. In the future work, the proposed algorithms will be applied to applications such as EMG based human motion recognition for prosthetic hands and human-robot skill transfer.

REFERENCES

- [1] S. Calinon, F. Guenter, and A. Billard, "On learning, representing, and generalizing a task in a humanoid robot," *IEEE Transactions on Systems, Man and Cybernetics Part B*, vol. 37, no. 2, p. 286, 2007.
- [2] S. Fels and G. Hinton, "Glove-talk: a neural network interface between a data-glove and a speech synthesizer," *IEEE Transactions on Neural Networks*, vol. 40(1), pp. 2–8, 1993.
- [3] S. Fels and G. Hinton, "Glove-TalkII-a neural-network interface which maps gestures to parallel formant speech synthesizer controls," *IEEE Transactions on Neural Networks*, vol. 9, no. 1, pp. 205–212, 1998.
- [4] Y. Sato, M. Saito, and H. Koike, "Real-time input of 3D pose and gestures of a user's hand and its applications for HCI," *Virtual Reality, 2001. Proceedings. IEEE*, pp. 79–86, 2001.
- [5] R. Zöllner, O. Rogalla, J. Zöllner, and R. Dillmann, "Dynamic grasp recognition within the framework of programming by demonstration," in *The 10th IEEE International Workshop on Robot and Human Interactive Communication (Roman)*, pp. 418–423, Citeseer.
- [6] D. Martinez and D. Kragic, "Modeling and recognition of actions through motor primitives," in *IEEE International Conference on Robotics and Automation*, pp. 1704–1709, 2008.
- [7] R. Natal, B. Dimuro, and A. Costa, "Hand gesture recognition in an interval fuzzy approach," *TEMA Tend. Mat. Apl. Comput.*, vol. 8, no. 1, pp. 21–31, 2007.
- [8] B. Bedregal, A. Costa, and G. Dimuro, "Fuzzy rule-based hand gesture recognition," *International Federation for Information Processing*, vol. 217, p. 285, 2006.
- [9] G. Heumer, H. Amor, M. Weber, and B. Jung, "Grasp recognition with uncalibrated data gloves-a comparison of classification methods," *Virtual Reality Conference, 2007. VR'07. IEEE*, pp. 19–26, 2007.
- [10] S. Calinon and A. Billard, "Incremental learning of gestures by imitation in a humanoid robot," *Proceedings of the ACM/IEEE international conference on Human-robot interaction*, pp. 255–262, 2007.
- [11] K. Kalgaonkar and B. Raj, "One-handed gesture recognition using ultrasonic Doppler sonar," in *Proceedings of the 2009 IEEE International Conference on Acoustics, Speech and Signal Processing-Volume 00*, pp. 1889–1892, IEEE Computer Society, 2009.
- [12] F. Chen, C. Fu, and C. Huang, "Hand gesture recognition using a real-time tracking method and hidden Markov models," *Image and Vision Computing*, vol. 21, no. 8, pp. 745–758, 2003.

- [13] K. Bernardin, K. Ogawara, K. Ikeuchi, and R. Dillmann, "A sensor fusion approach for recognizing continuous human grasping sequences using hidden Markov models," *IEEE Transactions on Robotics*, vol. 21, no. 1, pp. 47–57, 2005.
- [14] Z. Ju, H. Liu, X. Zhu, and Y. Xiong, "Dynamic grasp recognition using time clustering, gaussian mixture models and hidden markov models," *Journal of Advanced Robotics*, vol. 23, pp. 1359–1371, 2009.
- [15] A. Just and S. Marcel, "A comparative study of two state-of-the-art sequence processing techniques for hand gesture recognition," *Computer Vision and Image Understanding*, vol. 113, no. 4, pp. 532–543, 2009.
- [16] A. Dasgupta and A. Raftery, "Detecting features in spatial point processes with clutter via model-based clustering," *Journal of the American Statistical Association*, pp. 294–302, 1998.
- [17] C. Fraley and A. Raftery, "How many clusters? Which clustering method? Answers via model-based cluster analysis," *The Computer Journal*, vol. 41, no. 8, pp. 578–588, 1998.
- [18] B. Zhang, C. Zhang, and X. Yi, "Active curve axis Gaussian mixture models," *Pattern Recognition*, vol. 38, no. 12, pp. 2351–2362, 2005.
- [19] Z. Ju and H. Liu, "Applying fuzzy em algorithm with a fast convergence to gmms," in *Proc International Conference on Fuzzy Systems, World Congress on Computational Intelligence, Spain*, 2010.
- [20] A. Björck and Å. Björck, *Numerical methods for least squares problems*. Society for Industrial Mathematics, 1996.
- [21] J. C. Bezdek, *Pattern recognition with fuzzy objective function algorithms*. Kluwer Academic Publishers Norwell, MA, USA, 1981.
- [22] Z. Ju and H. Liu, "A modified expectation maximization algorithm for gaussian mixture models," in *Proc 2009 UK National Workshop on Computational Intelligence, Nottingham, UK*, 2009.
- [23] Z. Ju and H. Liu, "Recognizing hand grasp and manipulation through empirical copula," *International Journal of Social Robotics*, vol. 2, pp. 321–328, 2010.
- [24] T. Iberall, "Human prehension and dexterous robot hands," *The International Journal of Robotics Research*, vol. 16, no. 3, p. 285, 1997.