Human Hand Motion Analysis with Multisensory Information

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- Multiple-sensor Hand Motion Capture System
- Correlations of Finger Trajectories, Contact Force and the EMG signals
- Motion Recognition via EMG signals EMG: Electromyogram (肌电信号)
- Conclusion and Future Work

Multiple-sensor Hand Motion Capture System

•**Motion capturing module:** use different sensors to transfer the sensory information into digital signal recognisable to computers.

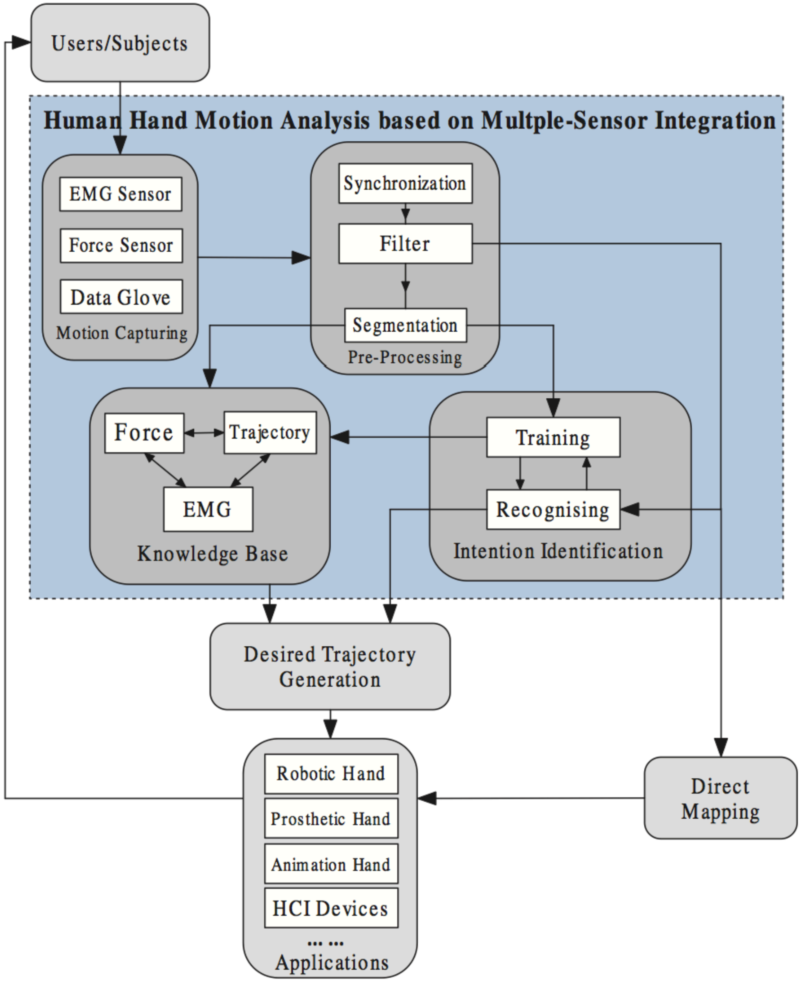
•**Preprocessing module:** synchronise and filter the original digital data and segment them into individual tasks.

•**Knowledge base module:** stores the human hand motion primitives, manipulation scenarios and correlations among the different sensory information.

•**Identification module:** use clustering and machine learning methods to train the motion models and recognise the new or testing sensory information.

•**Desired trajectory generation module:** generate the desired trajectories based on the human analysis framework for different applications.

•**Applications:** Robotic hands, Prosthetic hands, Animation Hands, Human-Computer Interaction and so on.

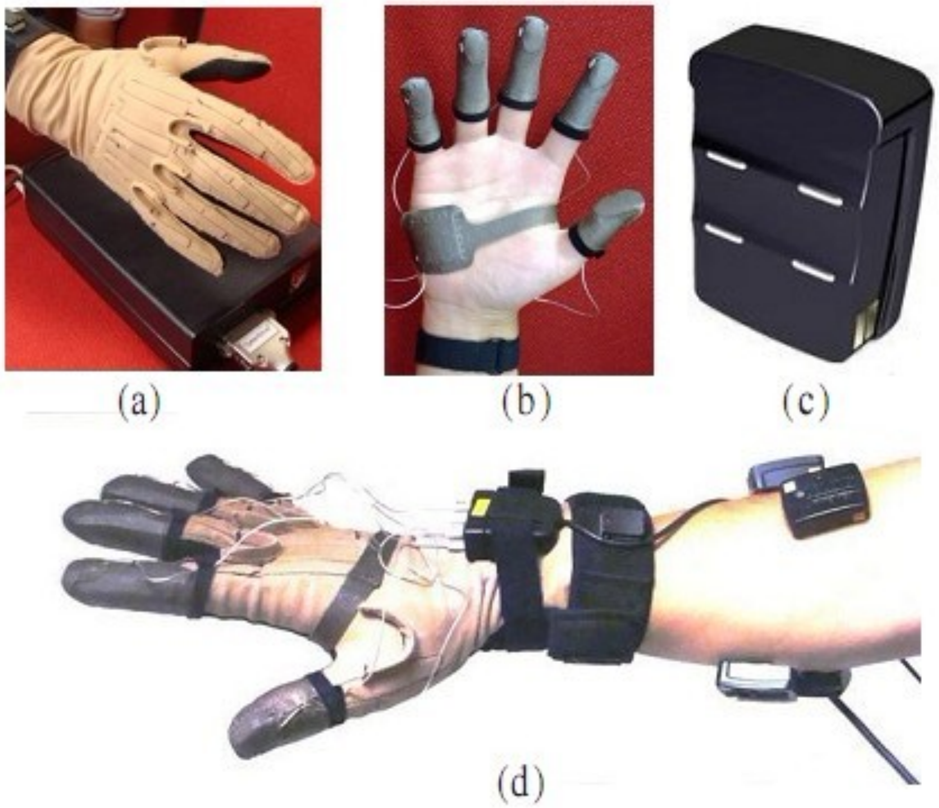


System Configuration

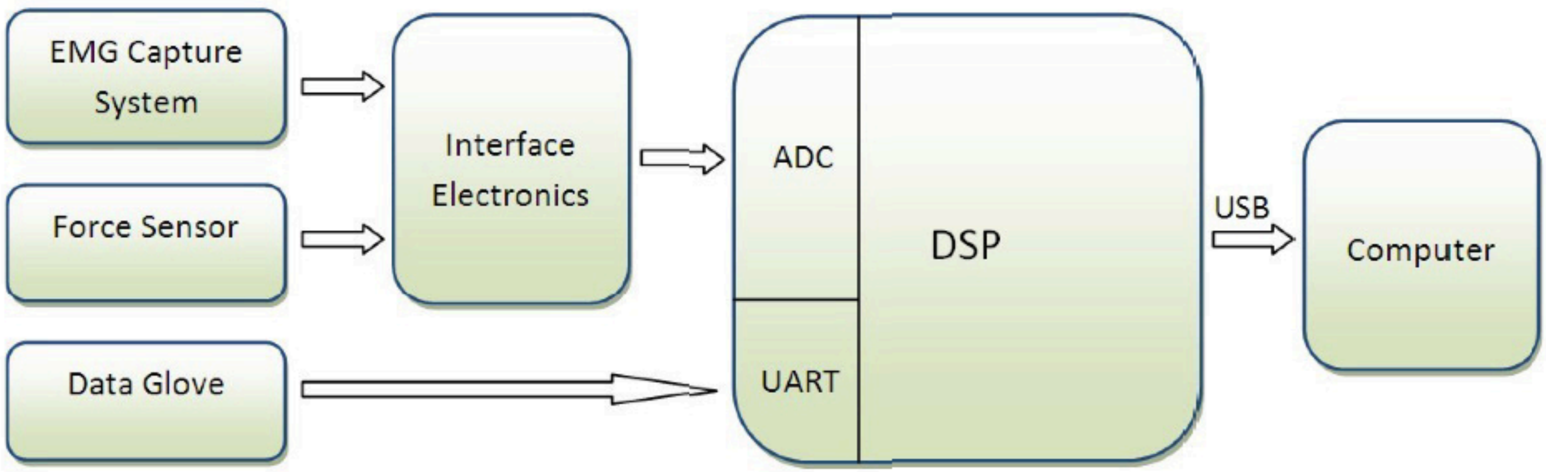
•**Cyber glove**: resistive bending sensors for 22 joint-angle measurements. 0.5 degree resolution and 150Hz sampling rate.

•**FingerTPS:** pressure sensors for 6 fingertips and palm. Resolution is 0.01lbs and sampling rate is 40 Hz

•**Trigno Wireless Sensors:** 16 channels with 48 accelerometer channels. Resolution is 16 bit and the max sampling rate is 4000Hz

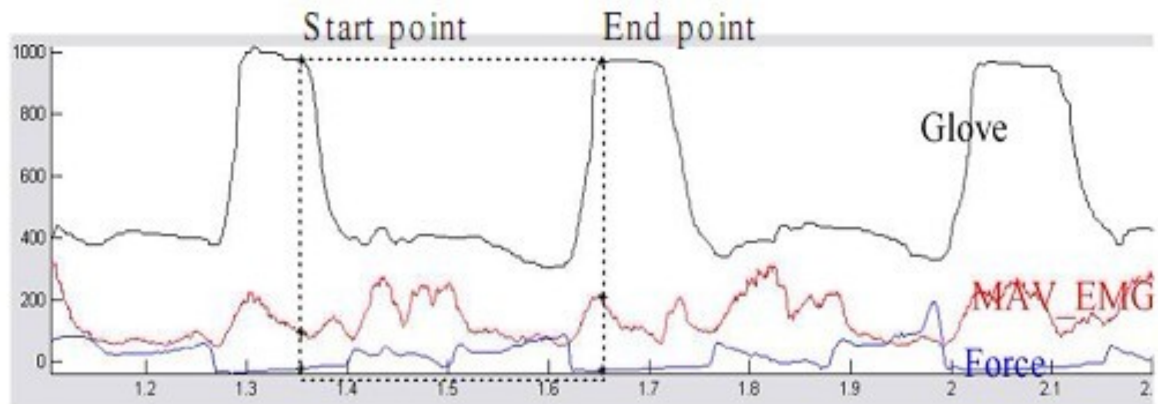


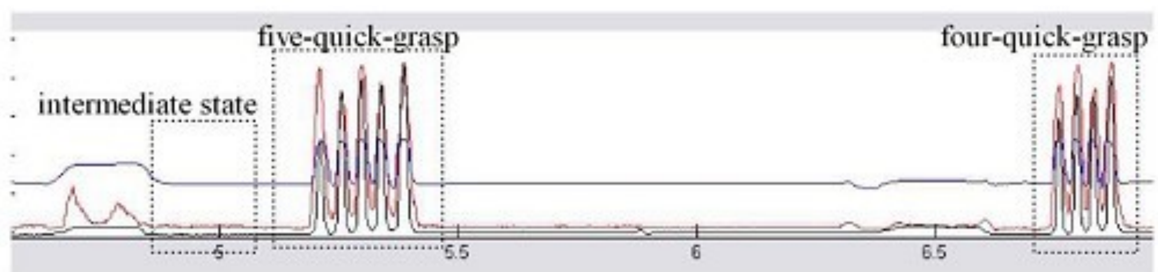
Synchronisation



Motion Segmentation

- **Intermediate state:** a flat hand with no strength.
- **Start point:** when the angle changes away from the intermediate state.
- **End point:** when the angle changes to the intermediate state.
- **'Five-quick-grasp':** when one type of the motions is finished.
- **'Four-quick-grasp':** when a fault motion is performed.

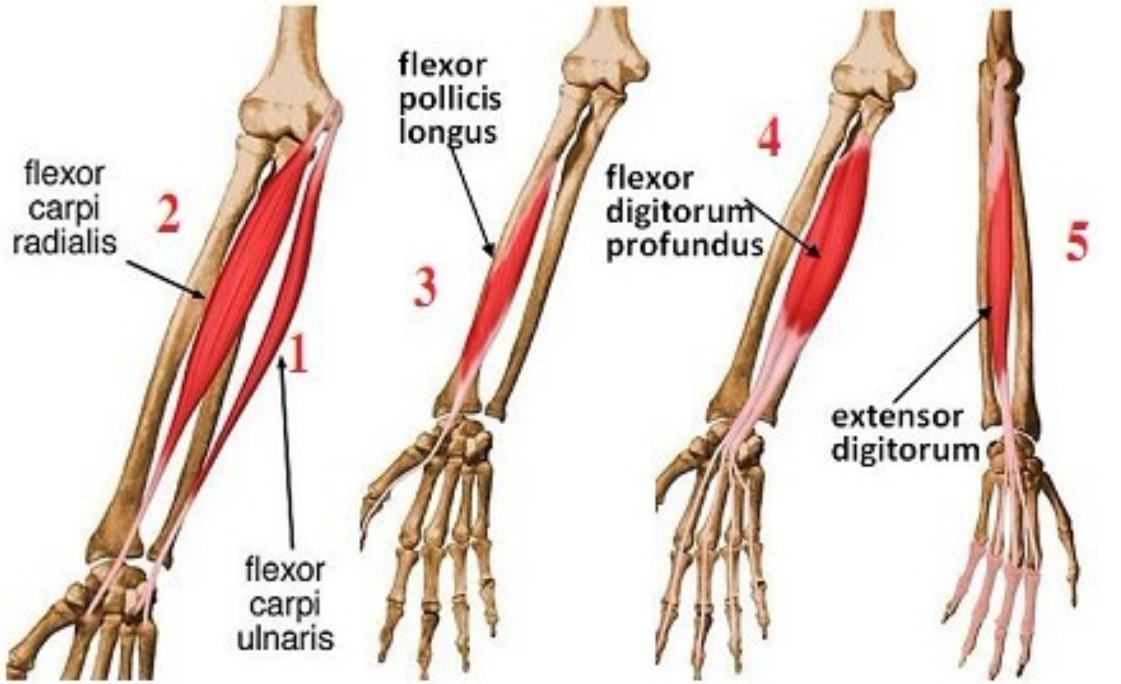




Data Capturing

•Electrodes location were selected according to the **musculoskeletal** system and confirmed by muscle specific contractions.

•**Visualization** on a computer screen guarantees stronger signals of the electrode locations.



Data Capturing

Grasps or in-hand manipulation

1) Grasp and lift a book using five fingers with the thumb abduction.
2) Grasp and lift a can full of rice using thumb, index finger and middle finger only.
3) Grasp and lift a can full of rice using five fingers with the thumb abduction.
4) Grasp and lift a big ball using five fingers.
5) Grasp and lift a disc container using thumb and index finger only.
6) Uncap and cap a marker pen using thumb, index finger and middle finger.
7) Open and close a pen box using five fingers.
8) Pick up a pencil using five fingers, flip it and place it on the table.
9) Hold and lift a dumbbell.
10) Grasp and lift a cup using thumb, index finger and middle finger.

Correlations of the Sensory Information

Spearman's rho is a non-parametric measure of statistical dependence between two variables, and it assesses how well the relationship between two variables can be described using a monotonic function.

The **copula** of a random vector can capture the properties of the joint distribution which are invariant under transformations of the univariate margins.

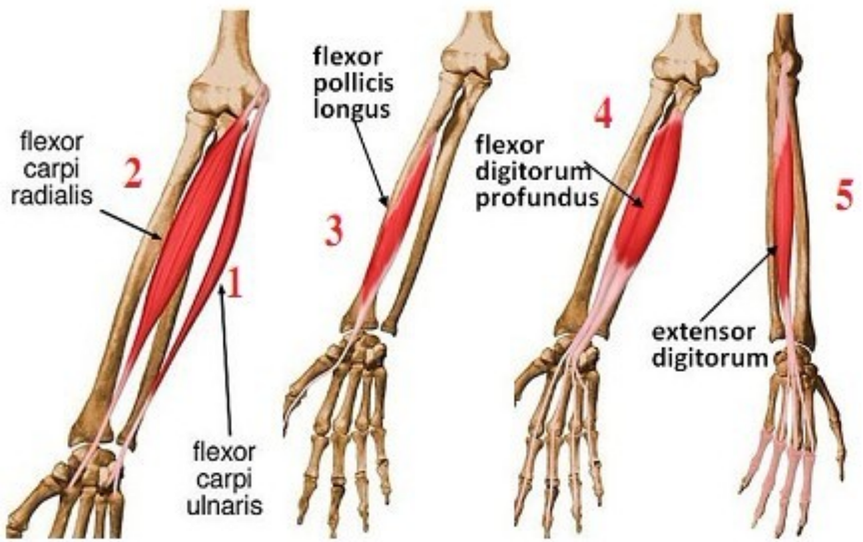
Correlations of the Sensory Information

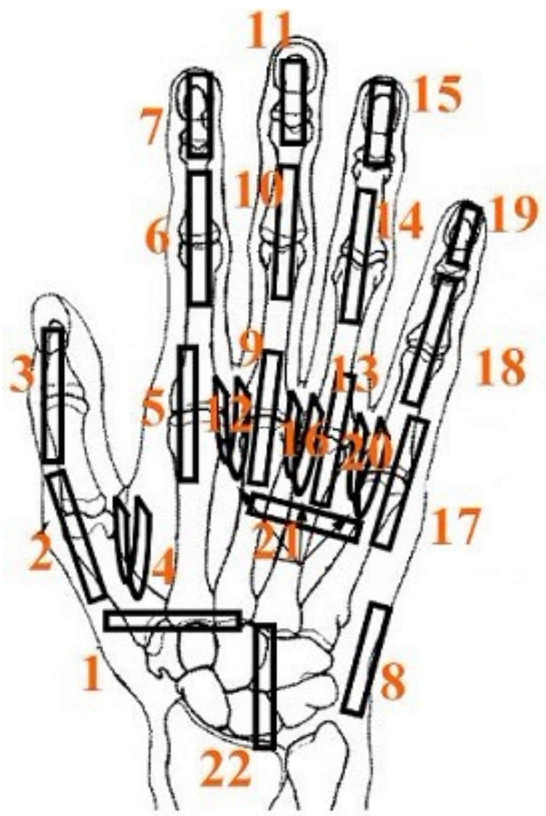
- *Let C_n and c_n denote, respectively, the Empirical Copula and Empirical Copula frequency function for the sample $\{(x_k, y_k)_{k=1}^{n}\}$. If ρ denotes the sample version of Spearman's rho, then*

$$\rho = \frac{12}{n^2-1}\sum_{i=1}^{n}\sum_{j=1}^{n}\left[C_n\left(\frac{i}{n}\cdot\frac{j}{n}\right) - \frac{i}{n}\cdot\frac{j}{n}\right]$$

- *Spearman's rho is used to measure two variables' association. According to the definition and theorem, we can estimate one-to-one correlations between variables using Empirical Copula based on Spearman's rho.*

Experiment Results





Relation of the Muscle Contraction and the Finger Tip Force

	thumb	index	middle	ring	little	palm
1	.32 (.08)	.26 (.09)	.28 (.10)	**.56 (.07)**	**.62 (.09)**	-.14 (.06)
2	.34 (.09)	**.41 (.08)**	**.56 (.06)**	.16 (.07)	.17 (.07)	.16 (.08)
3	**.73 (.09)**	.45 (.10)	.32 (.09)	.22 (.06)	.33 (.11)	-.12 (.06)
4	.33 (.09)	**.45 (.07)**	**.42 (.06)**	.21 (.05)	.32 (.07)	.02 (.11)
5	.15 (.10)	**-.42 (.08)**	**-.46 (.08)**	-.16 (.07)	-.25 (.10)	.09 (.09)

Relation of Muscle Contraction and the Finger Angle Trajectories

	Thumb Finger				Index Finger				Middle Finger		
	1	2	3	4	5	6	7	8	9	10	11
1	.14 (.06)	.23 (.07)	-.31 (.06)	-.25 (.04)	.11 (.06)	-.10 (.06)	.17 (.04)	.24 (.04)	.25 (.06)	.39 (.06)	.29 (.07)
2	.42 (.09)	-.34 (.07)	.04 (.06)	-.32 (.07)	**.55 (.10)**	**.41 (.05)**	**.49 (.05)**	.21 (.04)	**.81 (.09)**	**.48 (.07)**	**.47 (.08)**
3	**.73 (.04)**	**.68 (.12)**	**.71 (.07)**	-.52 (.04)	.33 (.03)	.55 (.10)	.48 (.09)	.05 (.03)	.43 (.07)	.39 (.08)	.31 (.04)
4	.00 (.05)	.17 (.07)	.28 (.08)	.11 (.06)	**.68 (.05)**	**.45 (.06)**	**.36 (.08)**	.44 (.05)	**.52 (.09)**	**.44 (.05)**	**.31 (.04)**
5	-.19 (.11)	.13 (.07)	-.10 (.08)	-.12 (.09)	**-.42 (.11)**	**-.31 (.05)**	**-.25 (.06)**	-.13 (.07)	**-.43 (.09)**	**-.21 (.10)**	**-.14 (.12)**

		Ring Finger				Little Finger					
	12	13	14	15	16	17	18	19	20	21	22
1	-.18 (.06)	**.63 (.06)**	**.51 (.06)**	**.40 (.06)**	.23 (.05)	**.83 (.06)**	**.49 (.06)**	**.48 (.07)**	.22 (.04)	-.06 (.08)	-.37 (.08)
2	.32 (.08)	-.07 (.06)	-.37 (.09)	-.38 (.05)	.26 (.06)	-.21 (.08)	-.36 (.09)	-.25 (.07)	-.17 (.05)	-.11 (.08)	-.43 (.07)
3	**.53 (.05)**	.18 (.08)	.43 (.03)	.51 (.05)	.51 (.05)	.21 (.06)	.48 (.03)	.52 (.08)	.31 (.07)	.19 (.10)	.10 (.10)
4	.21 (.06)	.30 (.08)	.01 (.05)	.19 (.05)	-.06 (.06)	.32 (.09)	.16 (.05)	.25 (.07)	.24 (.08)	.28 (.08)	-.16 (.06)
5	-.08 (.10)	.25 (.06)	-.02 (.13)	.04 (.09)	-.21 (.09)	.22 (.10)	-.14 (.11)	-.13 (.09)	-.24 (.06)	-.11 (.08)	.16 (.08)

Motion Recognition via EMG Intention

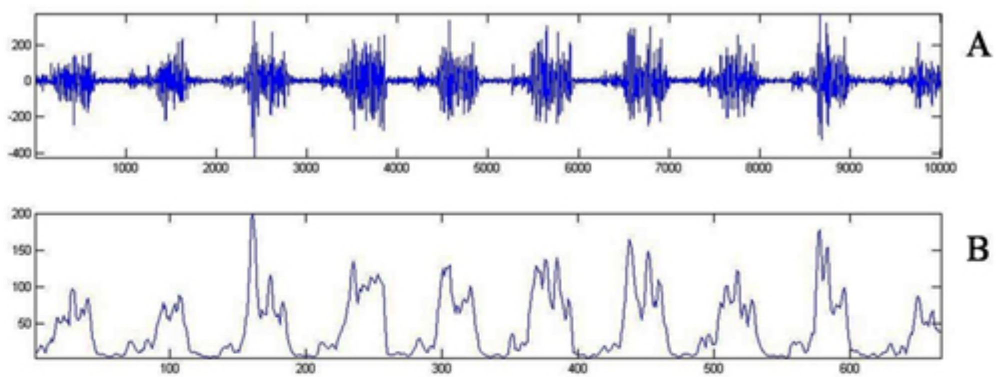
- Feature – Root Mean Square
- Fuzzy Gaussian Mixture Models
- Comparative Experimental Results

Motion Recognition via EMG Intention

Root Mean Square(RMS), modeled as amplitude modulated Gaussian random process, relates to the constant force and non-fatiguing contraction. Suppose the EMG signal is $f(t)$, where $1 \leq t \leq N$, N is the number of the sample points, then the RMS is given by

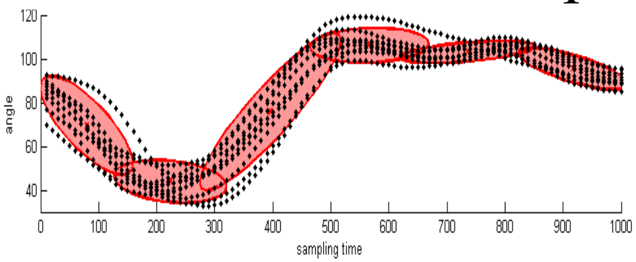
$$f_{rms}(t) = \sqrt{\frac{1}{2w+1} \sum_{i=t-w}^{t+w} f^2(i)}$$

where $2w+1$ denotes the length of the signal window



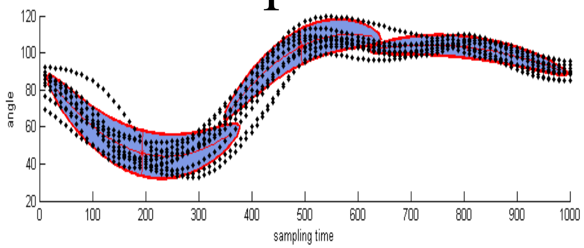
Fuzzy Gaussian Mixture Models

Faster but more components



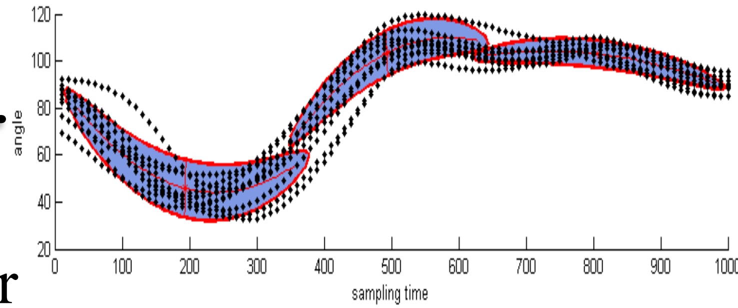
GMM

Fewer components but slower



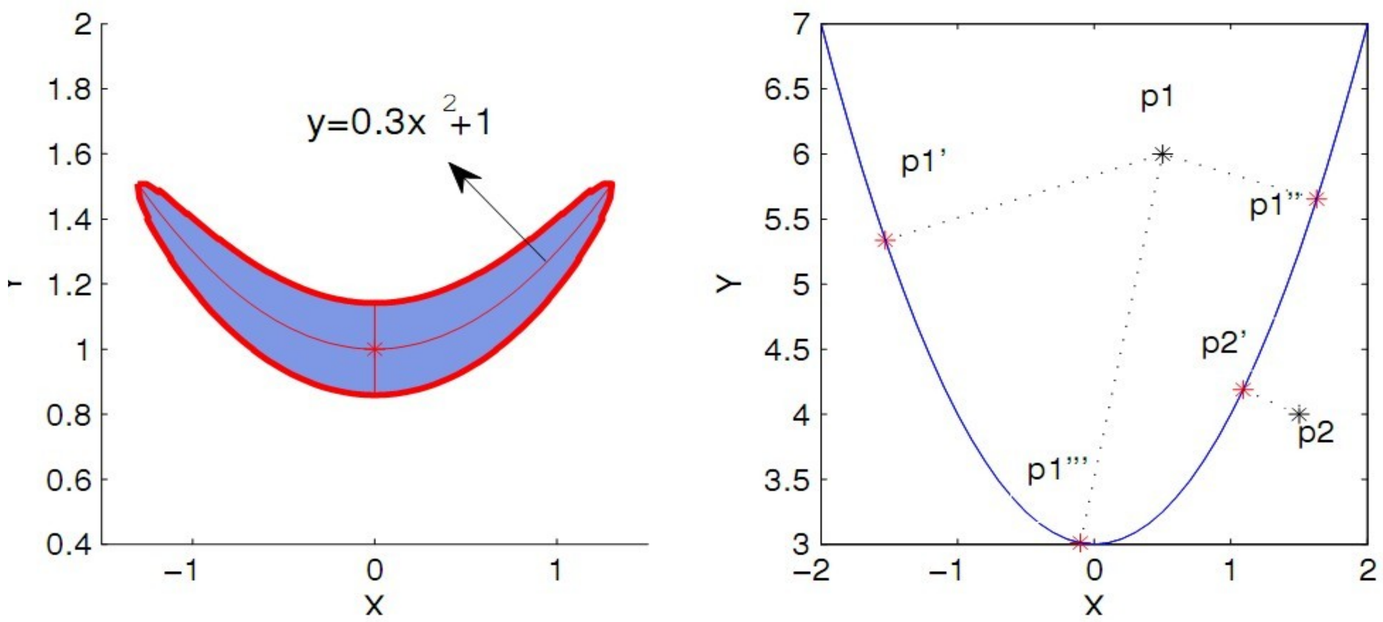
AcaGMM

Faster and fewer components



Fuzzy GMM

Bent Gaussian Distribution



EM Algorithm for FGMMs

- Compute "expected" classes of all data points for each class:

$$\mathrm{d}_{it} = \frac{1}{\alpha_i p_i(x_t|\theta_i)}$$

$$\mathrm{u}_{it} = \left[\sum_{j=1}^{k} \left(\frac{d_{it}}{d_{jt}}\right)^{\frac{2}{m-1}}\right]^{-1}$$

Fuzzy C-means

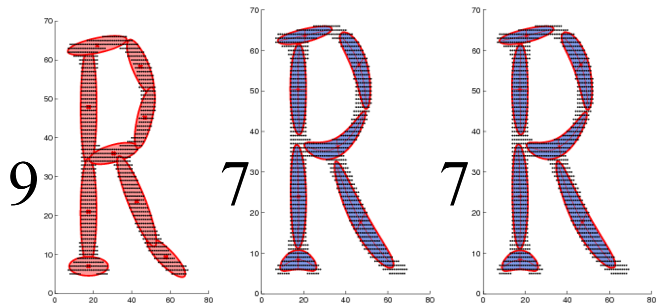
- Compute maximum likelihood given the data's class membership distributions:

$$\mu_i^{new} = \frac{\sum_{t=1}^{n} u_{it}^m x_t}{\sum_{t=1}^{n} u_{it}^m} + (Q_i^{new})^{-1} \underbrace{[0, b, 0, \cdots, 0]^T}_{d} + T_i^{new}$$

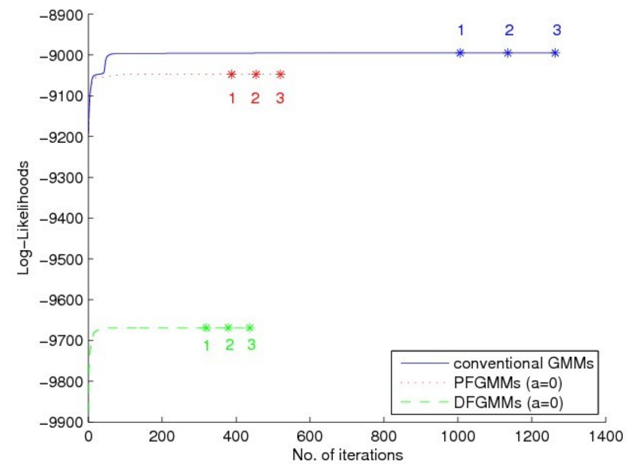
$$\Sigma_{ie}^{new} = \frac{\sum_{t=1}^{n} u_{it}^m \bar{L}_{te}^{(i)}}{\sum_{t=1}^{n} u_{it}^m} \qquad \textbf{(e=1,2)}$$

Active curve axis GMMs

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

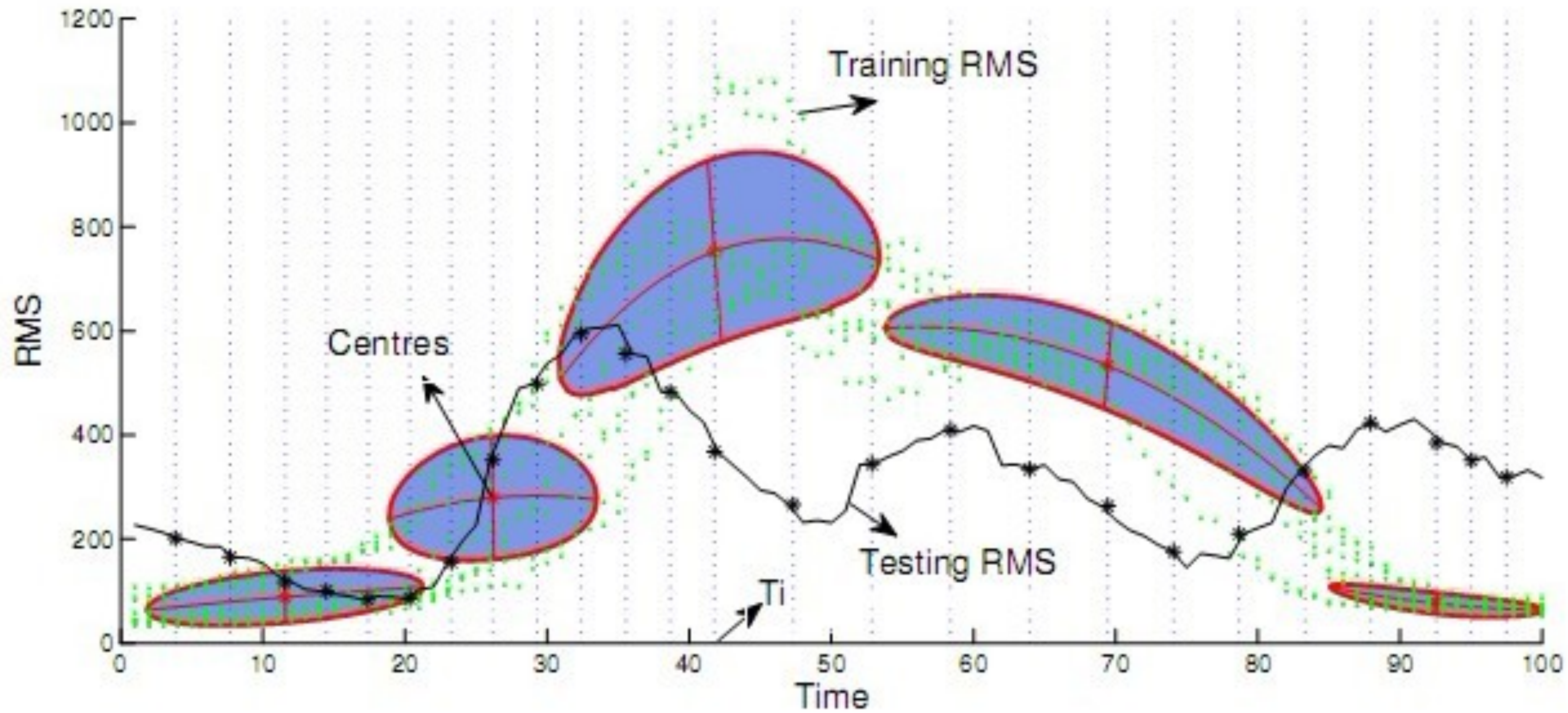


GMM | Probability Based **FGMM** | Distance Based **FGMM**



Character	NI/Time	CGMMs	PFGMMs (a = 0)	DFGMMs (a = 0)
‘6’, ‘8’, ‘a’, ‘B’, ‘R’	NI	100%	53.33%	43.11%
	Time	100%	69.29%	47.63%
	NI/TIME	GGMMs	PFGMMs (|a| ≥ 0)	DFGMMs (|a| ≥ 0)
	NI	100%	48.48%	47.70%
	Time	100%	51.12%	48.71%

FGMM Training and Modeling



Motion Recognition Methods

- Gaussian Mixture Models (GMMs) and FGMMs

  The parameter for GMM/FGMM is the number of the component ranging from 2 to 20 with increments of one and is selected with their best performance.

- Support Vector Machine

  Parameters for SVM are the kernel parameter ranging from 1 to 10 with increments of one and penalty cost whose range is from 1 to 501 with increments of 50.

  These parameters are selected with their best performance.

Experiment Results

	$Motion_1$	$Motion_2$	$Motion_3$	$Motion_4$	$Motion_5$	$Motion_6$	$Motion_7$	$Motion_8$	$Motion_9$	$Motion_{10}$
Motion_1	0.97	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
Motion_2	0.00	0.80	0.01	0.19	0.00	0.00	0.00	0.00	0.00	0.00
Motion_3	0.00	0.00	0.93	0.04	0.00	0.00	0.03	0.01	0.00	0.00
Motion_4	0.00	0.01	0.05	0.81	0.00	0.00	0.09	0.03	0.01	0.00
Motion_5	0.00	0.00	0.00	0.05	0.95	0.00	0.00	0.00	0.00	0.00
Motion_6	0.00	0.00	0.00	0.00	0.01	0.97	0.00	0.01	0.00	0.00
Motion_7	0.00	0.00	0.00	0.00	0.00	0.05	0.90	0.01	0.04	0.00
Motion_8	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.97	0.00	0.00
Motion_9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
Motion_10	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.96

FGMM (92.75%)

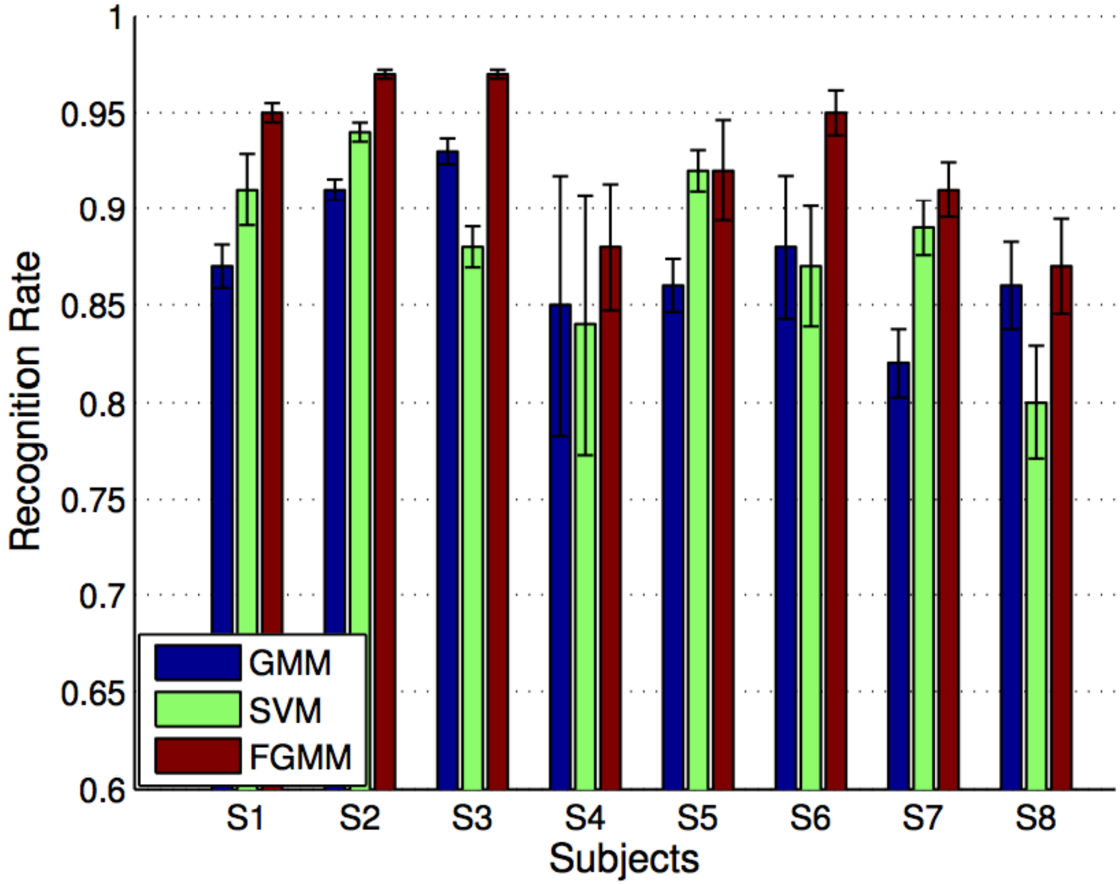
	$Motion_1$	$Motion_2$	$Motion_3$	$Motion_4$	$Motion_5$	$Motion_6$	$Motion_7$	$Motion_8$	$Motion_9$	$Motion_{10}$
Motion_1	0.94	0.00	0.00	0.04	0.00	0.00	0.00	0.03	0.00	0.00
Motion_2	0.00	0.82	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00
Motion_3	0.03	0.01	0.86	0.05	0.01	0.01	0.01	0.01	0.00	0.00
Motion_4	0.00	0.15	0.03	0.70	0.00	0.00	0.09	0.03	0.01	0.00
Motion_5	0.00	0.00	0.00	0.01	0.93	0.03	0.01	0.00	0.03	0.00
Motion_6	0.00	0.03	0.00	0.00	0.00	0.95	0.00	0.00	0.03	0.00
Motion_7	0.04	0.01	0.05	0.01	0.00	0.06	0.76	0.01	0.04	0.01
Motion_8	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.94	0.05	0.00
Motion_9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
Motion_10	0.00	0.00	0.00	0.01	0.01	0.05	0.01	0.00	0.00	0.91

SVM (88.75%)

	$Motion_1$	$Motion_2$	$Motion_3$	$Motion_4$	$Motion_5$	$Motion_6$	$Motion_7$	$Motion_8$	$Motion_9$	$Motion_{10}$
Motion_1	0.93	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.04	0.00
Motion_2	0.00	0.85	0.00	0.13	0.00	0.03	0.00	0.00	0.00	0.00
Motion_3	0.01	0.04	0.91	0.01	0.00	0.01	0.01	0.00	0.00	0.00
Motion_4	0.04	0.16	0.09	0.63	0.00	0.00	0.05	0.04	0.00	0.00
Motion_5	0.00	0.00	0.03	0.03	0.89	0.01	0.00	0.00	0.01	0.04
Motion_6	0.00	0.01	0.00	0.00	0.03	0.94	0.00	0.01	0.01	0.00
Motion_7	0.00	0.04	0.03	0.03	0.00	0.05	0.75	0.04	0.05	0.03
Motion_8	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.94	0.04	0.00
Motion_9	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.97	0.00
Motion_10	0.00	0.00	0.00	0.03	0.00	0.00	0.01	0.04	0.00	0.93

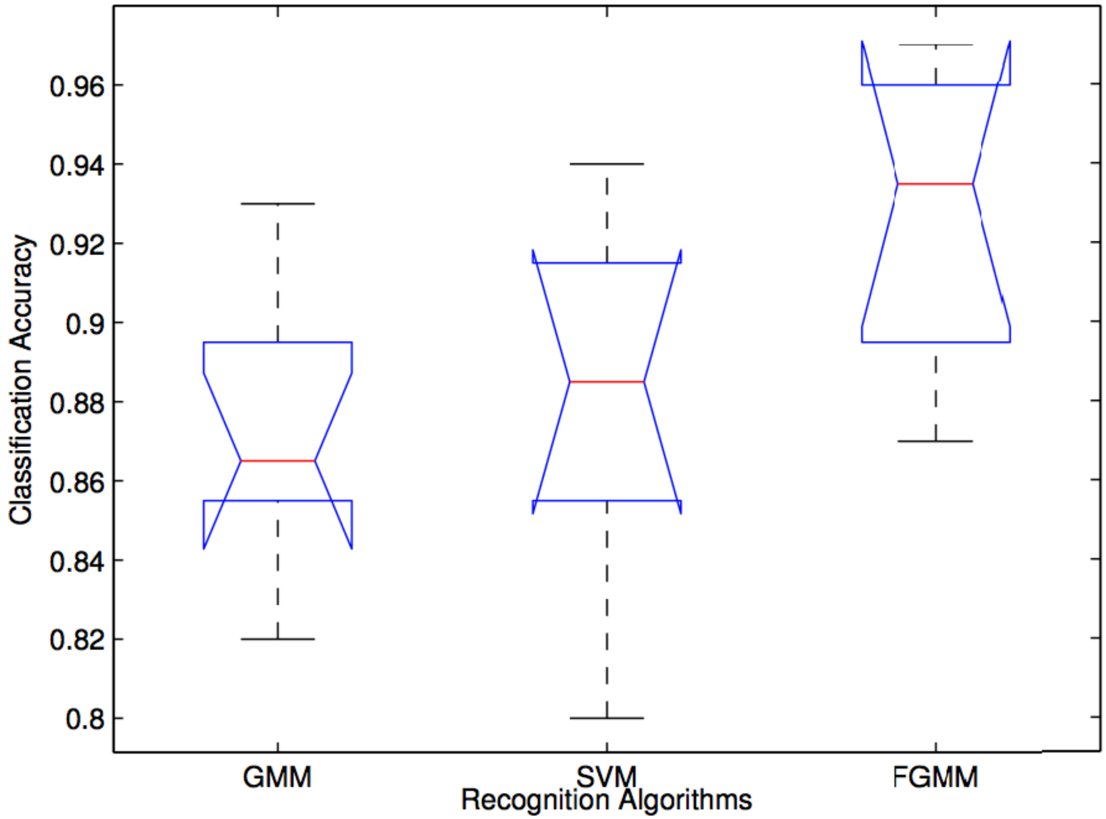
GMM (87.25%)

Experiment Results



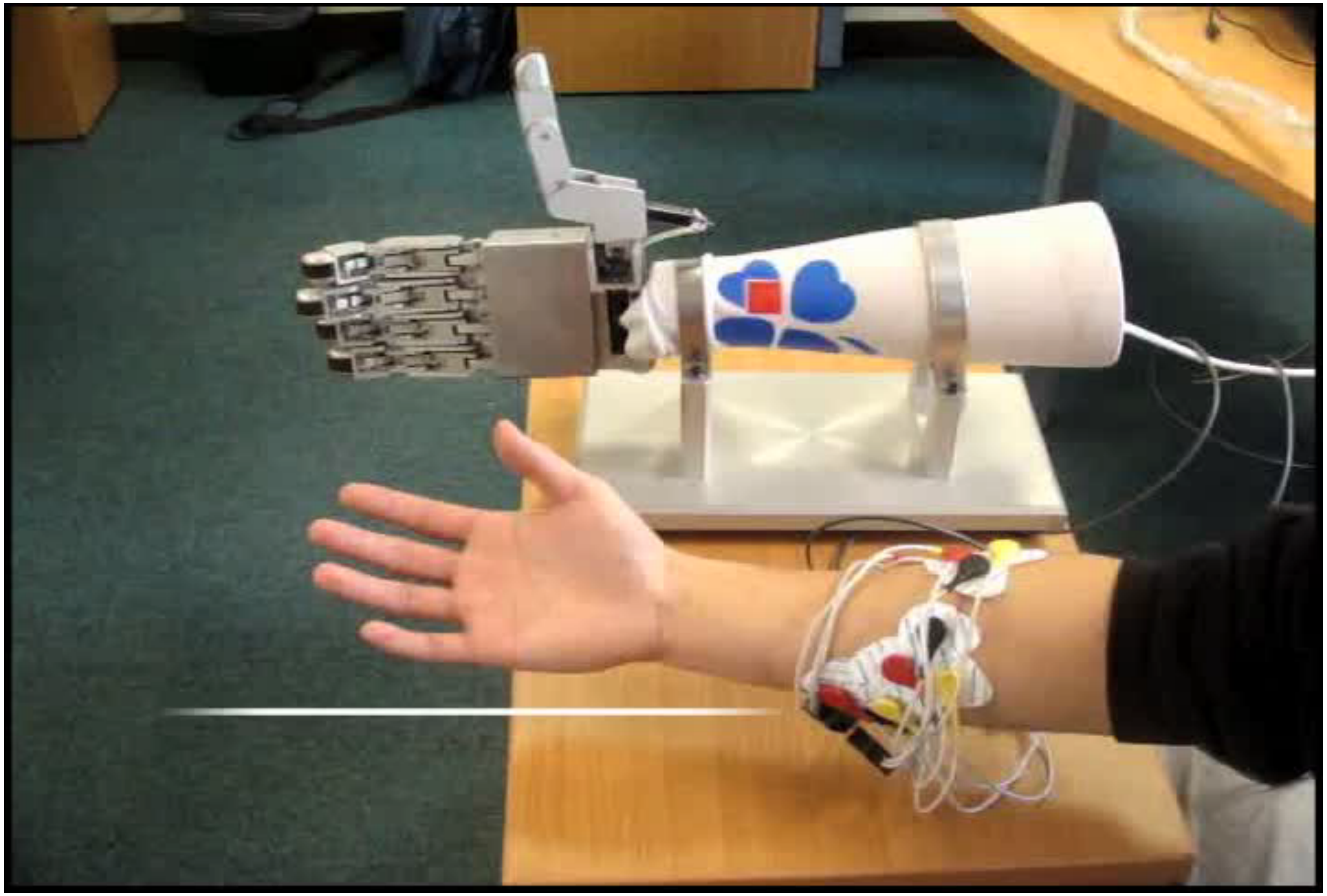
Recognition results with means and variances of different subjects using different methods

Experiment Results



Box plot results for the different classifiers for all subjects

Control Prosthetic Hand



Conclusion

- An integrated framework with multiple sensory information for analysing human hand motions has been proposed.
- Motion capturing module, signal preprocessing module, knowledge base module and intention recognition module have all been investigated.
- This platform has potential applications in robotics, biomedical engineering, PbD and HCI.
- Future work will be targeted to apply this framework into automatically controlling prosthetic hands such as the ilimb hand from the Touch Bionics.

Thanks for your time!