Xian Zang, Felipe P. Vista IV, Kil To Chong, 2014. Fast global kernel fuzzy c-means clustering algorithm for consonant/vowel segmentation of speech signal. *Journal of Zhejiang University-SCIENCE C (Computers & Electronics)*, **15**(7):551-563. [doi:10.1631/jzus.C1300320]

Fast global kernel fuzzy c-means clustering algorithm for consonant/vowel segmentation of speech signal

Key words: Fuzzy c-means (FCM) clustering, Kernel method, Global optimization, Consonant/vowel segmentation

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Motivation

- Overcome two shortcomings of fuzzy c-means (FCM)
  - *sensitivity to initialization*
  - *inability to use non-linear separable data*

- Reduce the computational complexity when providing a solution for the shortcomings given above.

Method

➢ Global Kernel Fuzzy C-Means-F (**GKFCM-F**)

- *overcomes the two shortcomings of FCM*

- *integrates the advantages of KFCM-F and GFCM to realize a near-optimal solution for non-linearly separable data*

➢Fast Global Kernel Fuzzy C-Means-F (**FGKFCM-F**)

- *an accelerating scheme that chooses the set of initial memberships, with KFCM-F executed only once at each stage*

- *does not significantly affect the solution quality*

GKFCM-F and FGKFCM-F

Input:

1. $\boldsymbol{X}=\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_i, \ldots, \boldsymbol{x}_N\}$, $\boldsymbol{x}_i \in \Re^d$, the dataset;
2. C, $1<C\leq N$, the number of clusters;
3. $\varepsilon>0$, the stopping criterion of algorithm;
4. $\mu^{(0)}=\{\mu_1^{(0)}, \mu_2^{(0)}, \ldots, \mu_C^{(0)}\}$, the initials of memberships;
5. $m>1$, the weighting exponent;
6. σ, the GRBF kernel parameter.

Output:

1. $\tilde{\boldsymbol{v}}=\{\tilde{v}_1, \tilde{v}_2, \ldots, \tilde{v}_C\}$, the final cluster prototypes;
2. $\mu=\{\mu_1, \mu_2, \ldots, \mu_C\}$, the final memberships

GKFCM-F Algorithm

1. Compute $\tilde{v}^*(1)$ using Eq. (23) with initial position $\tilde{v}(1)$ placed at data point which minimizes Eq. (24);
2. **for** k=2 to C **do**
3. **for** n=1 to N **do**
4. Set initial state

$$\tilde{v}^{n(0)}(k) = \{\tilde{v}_1(k), \tilde{v}_2(k), \ldots, \tilde{v}_{k-1}(k), \tilde{v}_k(k)\}$$
$$= \{\tilde{v}_1^*(k-1), \tilde{v}_2^*(k-1), \ldots, \tilde{v}_{k-1}^*(k-1), x_n\};$$

5. Set initial memberships $\mu^{n(0)}(k)$ with respect to $\tilde{v}^{n(0)}(k)$ using Eq. (25);
6. $\mu^n(k) \leftarrow KFCM\text{-}F(X, k, \varepsilon, m, \sigma^2, \mu^{n(0)}(k))$
7. **end**
8. $l = \arg\min_{1 \le n \le N} J^{\Phi}(\mu^n(k))$, using Eq. (23)
9. $\mu^*(k) \leftarrow \mu^l(k)$;
10. $\tilde{v}^{(0)}(k) \leftarrow \tilde{v}^{l(0)}(k)$;
11. Let s = 1;
12. Update $\tilde{v}^{(s)}(k)$ with $\tilde{v}^{(s-1)}(k)$ using Eq. (23);
13. If $\|\tilde{v}^{(s)}(k) - \tilde{v}^{(s-1)}(k)\| < \varepsilon$,
14. STOP and $\tilde{v}^*(k) \leftarrow \tilde{v}^{(s)}(k)$;
15. Else $s = s + 1$ and return to Step 12;
16. **end**
17. $\tilde{\boldsymbol{v}} \leftarrow \tilde{\boldsymbol{v}}^*(C), \boldsymbol{\mu} \leftarrow \boldsymbol{\mu}^*(C)$.

FGKFCM-F Algorithm

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$$\tilde{v}^{n(0)}(k) = \{\tilde{v}_1(k), \tilde{v}_2(k), \ldots, \tilde{v}_{k-1}(k), \tilde{v}_k(k)\}$$
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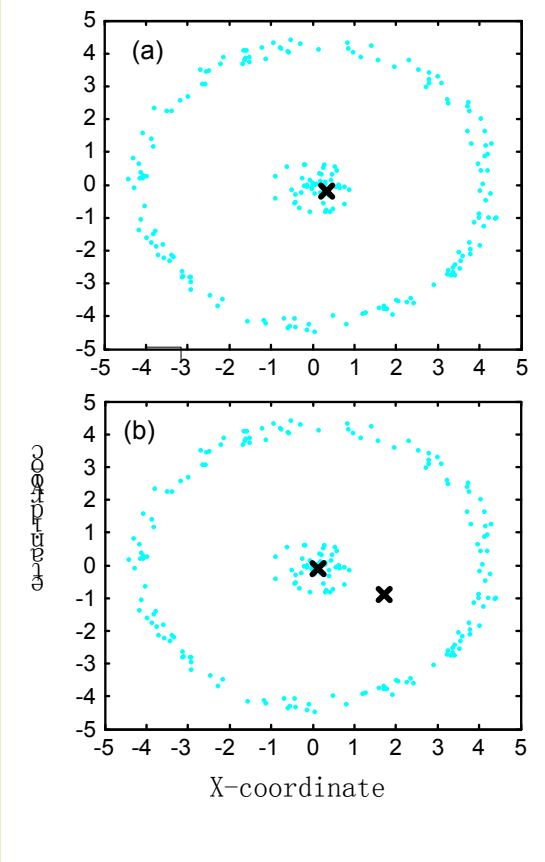
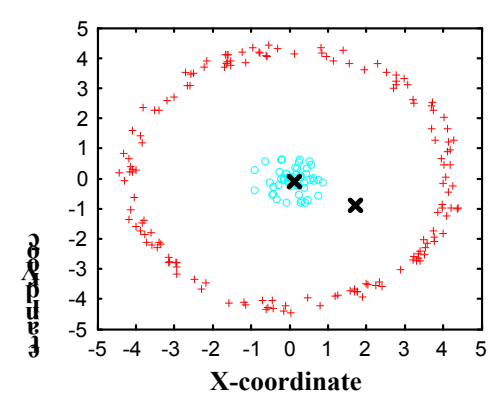
5. Set initial memberships $\mu^{n(0)}(k)$ with respect to $\tilde{v}^{n(0)}(k)$ using Eq. (25);
6. **end**
7. $l = \arg\min_{1 \le n \le N} J^{\Phi}(\mu^n(k))$, using Eq. (19)
8. $\mu^n(k) \leftarrow KFCM\text{-}F(X, k, \varepsilon, m, \sigma^2, \mu^{n(0)}(k))$
9. $\tilde{v}^{(0)}(k) \leftarrow \tilde{v}^{l(0)}(k)$;
10. Let s = 1;
11. Update $\tilde{v}^{(s)}(k)$ with $\tilde{v}^{(s-1)}(k)$ using Eq. (23);
12. If $\|\tilde{v}^{(s)}(k) - \tilde{v}^{(s-1)}(k)\| < \varepsilon$,
13. STOP and $\tilde{v}^*(k) \leftarrow \tilde{v}^{(s)}(k)$;
14. Else $s = s + 1$ and return to Step 12;
15. **end**
16. $\tilde{\boldsymbol{v}} \leftarrow \tilde{\boldsymbol{v}}^*(C)$, $\boldsymbol{\mu} \leftarrow \boldsymbol{\mu}^*(C)$.

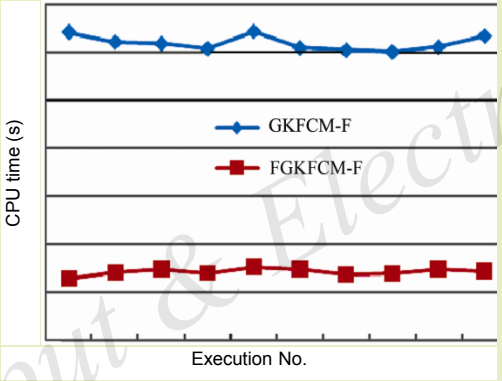
Simulation Results



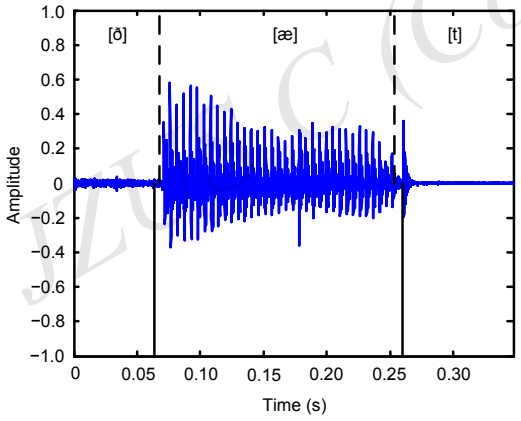
Optimal approximate cluster prototypes (×) obtained at each intermediate step in FGKFCM-F



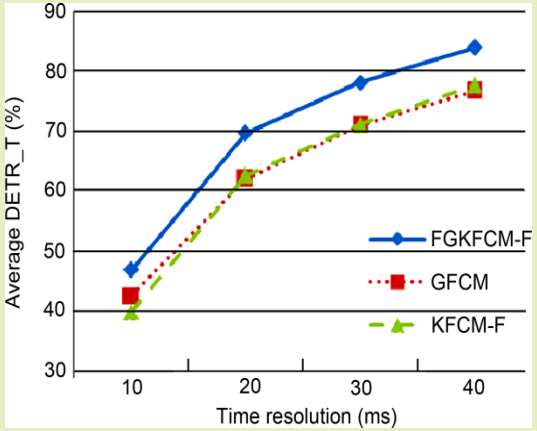
Clustering result for ball-ring dataset using FGKFCM-F



Computer processing time for GKFCM-F and FGKFCM-F



Consonant/vowel (C/V) segmentation results for the word "that" using FGKFCM-F (matching error: 3.9 ms; 6.8 ms)



Average DETR_T of GFCM, KFCM-F, and FGKFCM-F

Consonant/vowel (C/V) segmentation results for 1000 words using FGKFCM-F

Word category	Reference points No.	DETR_T (% within ms)			
		±10	±20	±30	±40
Monosyllable*					
C^+VC^+	800	43.75	66.75	76.63	84.00
VC^+	200	75.00	90.50	95.50	98.50
C^+V	200	51.00	93.50	98.00	99.50
Polysyllable	500	38.60	56.6	65.80	72.00

* C indicates a consonant, V indicates a vowel, and + denotes one or more consecutive consonants

Conclusions

- Propose a novel clustering scheme (FGKFCM-F) that derives a near-optimal solution by solving all intermediate problems using kernel-based fuzzy C-means-F (KFCM-F) as the local search procedure.
- Overcome shortcomings of FCM: (1) sensitivity to initialization, and (2) inability to use non-linear data.
- Reduce computational complexity without significantly affecting solution quality.
- Experimental results show that FGKFCM-F is superior to other methods for both the artificial and the real-world datasets of speech signal.