





A Comparative Study of Multi-Objective Evolutionary Trace Transform Methods for Robust Feature Extraction

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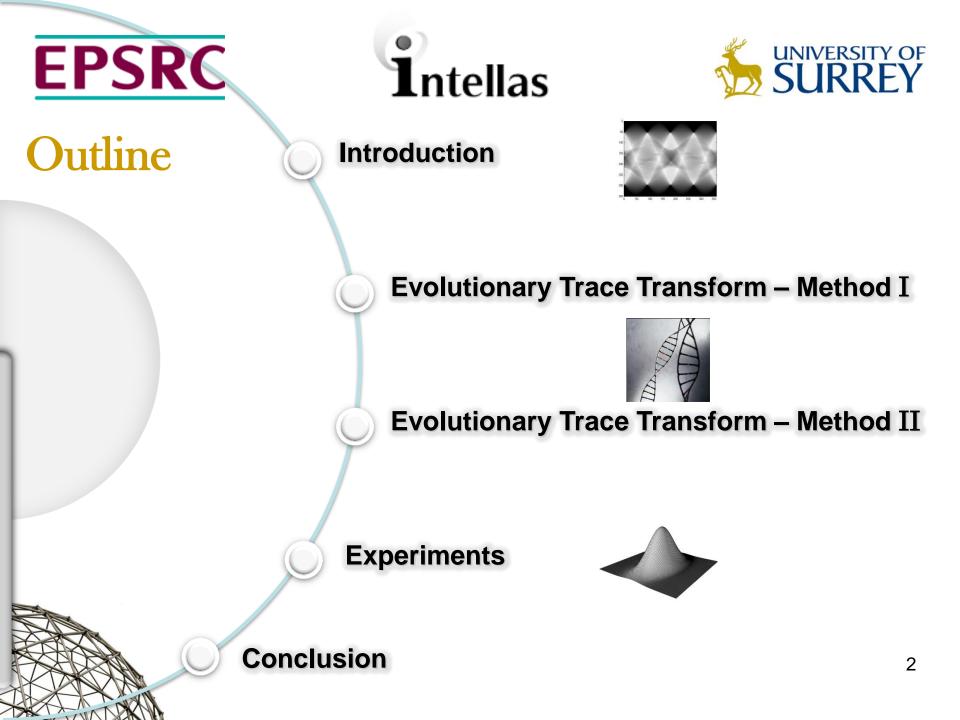
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22nd March 2013

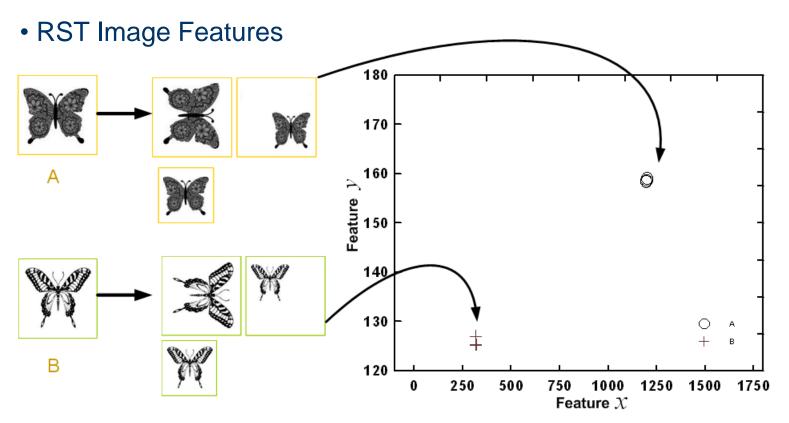








Introduction

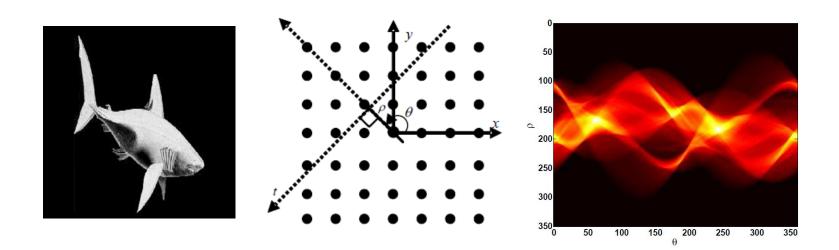








• Trace Transform^[1] and Theory of Triple Features





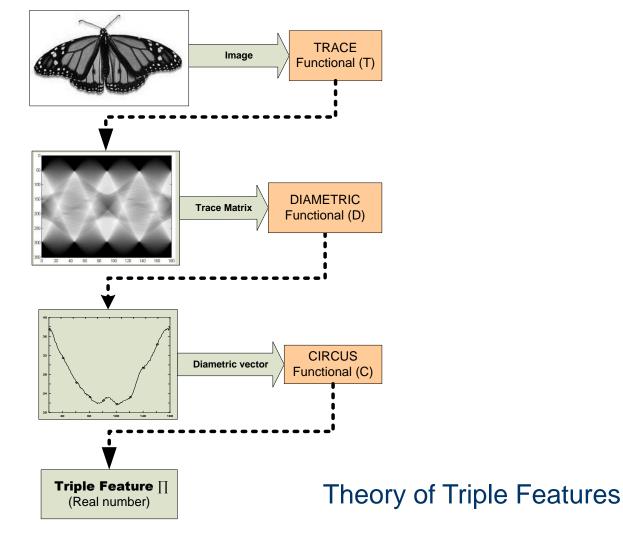
[1] Kadyrov, A., Petrou, M.: The trace transform and its applications. IEEE Transactions on Pattern Analysis and Machine Intelligence 23(8), 811–828 (2001)





Intellas







[2] Albukhanajer, W.A., Jin, Y., Briffa, J.A., Williams, G.: Evolutionary Multi-Objective Optimization of Trace Transform for Invariant Feature Extraction. In: 2012 IEEE Congress on Evolutionary Computation, CEC, Brisbane, Australia, June.10-15, pp. 401–408 (2012)







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• Evolutionary Trace Transform (ETT)^[2]

Table	1.	List	of	some	Trace	functional	

No.	Functional	Description
1	$\int f(t)dt$	Radon transform
2	$\frac{\int \left f(t)' \right dt}{\left(\int \left f(t) \right ^p dt \right)^q}$	Integral of Gradient
3	$\left(\int \left \dot{f}(t)\right)\right ^{p} dt\right)^{q}$	p-Norm, $p = 0.5, q = 1/p$
4	max - min(f(x))	Maximum-minimum of the function

• Using NSGA-II^[3] and Pareto front concept on Trace Functionals

[2] Albukhanajer, W.A., Jin, Y., Briffa, J.A., Williams, G.: Evolutionary Multi-Objective Optimization of Trace Transform for Invariant Feature Extraction. In: 2012 IEEE Congress on Evolutionary Computation, CEC, Brisbane, Australia, June 10-15, pp. 401–408 (2012)

[3] K. Deb, Multi-Objective Optimization using Evolutionary Algorithms, 1st ed. England: John Wiley & Sons. Ltd, 2002.







ETT - Method I

Chromosome Structure (Integer):

T1	D1	C1	θ1
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- T: Trace Functional
- D: Diametric Functional
- C: Circus Functional;
- Θ: Max number of Directions
- •Using NSGA-II and Pareto front concept to search 'good' Trace Functionals combinations to minimise the fitness functions in 1D feature space (One triple feature).
- Fitness:

$$f_1 = S_w^I$$
(1a)
$$f_2 = 1/(S_b^I + \epsilon)$$
(1b)

where ϵ is a small quantity to avoid division by zero. S_w^I and S_b^I are the within-class variance and between-class variance defined in (2):







$$S_w^I = \sum_{k=1}^K \sum_{j=1}^{N_k} (x_{jk} - \mu_k^x)^2$$
(2a)
$$S_b^I = \sum_{k=1}^K (\mu_k^x - \mu^x)^2$$
(2b)

where

$$\mu_k^x = \frac{1}{N_k} \sum_{j=1}^{N_k} x_{jk}, \ \mu^x = \frac{1}{K} \sum_{k=1}^K \mu_k^x$$

and K: number of classes, N_k : number of samples in class k, μ_k^x : mean of class k of x triple features, x_{jk} : the j^{th} sample of class k of x triple features, and μ^x : mean of all classes of x triple features.







ETT – Method II

Chromosome Structure (Integer):

T1	D1	C1	θ1	T2	D2	C2	θ2	
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Double length Chromosome

- Using NSGA-II and Pareto front concept to search 'good' Trace Functionals pair to minimise the fitness functions in 2D feature space (Two Triple features).
- Fitness:

$$f_1 = S_w^{II}$$
(3a)
$$f_2 = 1/(S_b^{II} + \epsilon)$$
(3b)









$$S_w^{II} = \sum_{k=1}^K \sum_{j=1}^{N_k} (x_{jk} - \mu_k^x)^2 + (y_{jk} - \mu_k^y)^2$$
(4a)
$$S_b^{II} = \sum_{k=1}^K (\mu_k^x - \mu^x)^2 + (\mu_k^y - \mu^y)^2$$
(4b)

where

$$\mu_k^x = \frac{1}{N_k} \sum_{j=1}^{N_k} x_{jk}, \\ \mu_k^y = \frac{1}{N_k} \sum_{j=1}^{N_k} y_{jk}, \\ \mu^x = \frac{1}{K} \sum_{k=1}^K \mu_k^x, \\ \mu^y = \frac{1}{K} \sum_{k=1}^K \mu_k^y$$

and K: number of classes, N_k : number of samples in class k, μ_k^x : mean of class k of x triple features, μ_k^y : mean of class k of y triple features, x_{jk} : the j^{th} sample of class k of x triple features, y_{jk} : the j^{th} sample of class k of y triple features, μ^x : mean of all classes of x triple features and μ^y : mean of all classes of y triple features.







Experiments

Elitist NSGA-II operations: Method I&II

- Selection:
 - 1) Tournament
 - 2) Pareto-front assignment
 - 3) Crowding Distance
- Uniform Crossover
- Uniform Mutation

Table 2. Parameter Set-up for method I and II

Parameter	Value
Population size N_p	150
Mutation probability	0.125
Crossover probability	0.9
Number of generations	200
έ	10^{-5}









- The search space consists of
 - 1) 14 Trace Functionals (T)
 - 2) Six Diametric Functionals (D)
 - 3) Six Circus Functionals (C)
 - 4) Θ takes a value between [180 360]

for each chromosome in Method I &II.





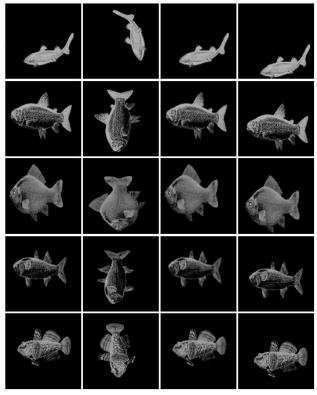




- Five images of low resolution (64x64) from fish database plus their rotated, scaled and translated versions are used during the evolutionary stage
- Offline Evolution: 200 generations.
- NSGA-II implemented using SHARK Machine Learning Library^[4]

[4] Christian Igel, Verena Heidrich-Meisner, and Tobias Glasmachers. <u>Shark</u>. Journal of Machine Learning Research 9, pp. 993-996, 2008

http://image.diku.dk/shark



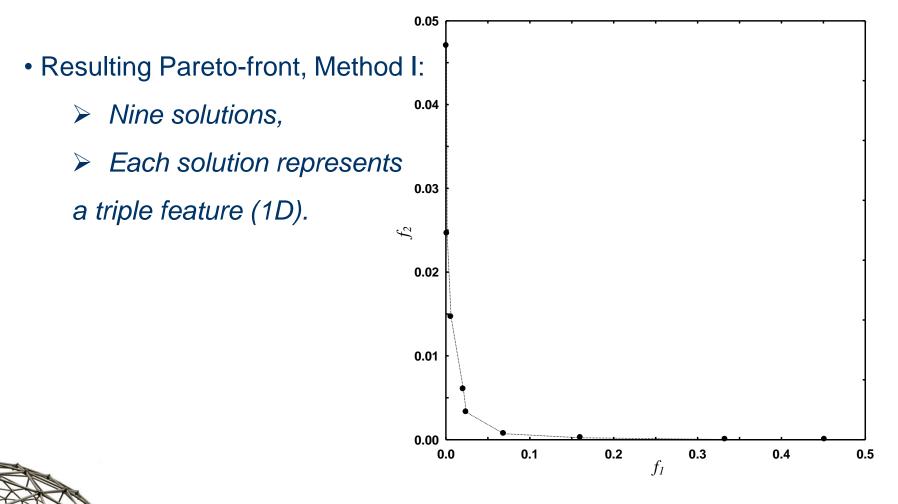
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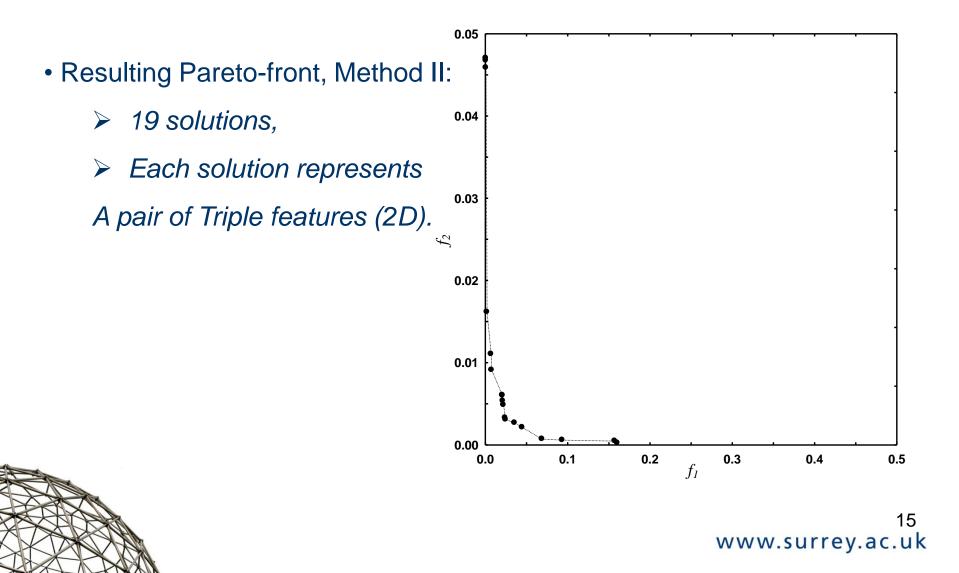








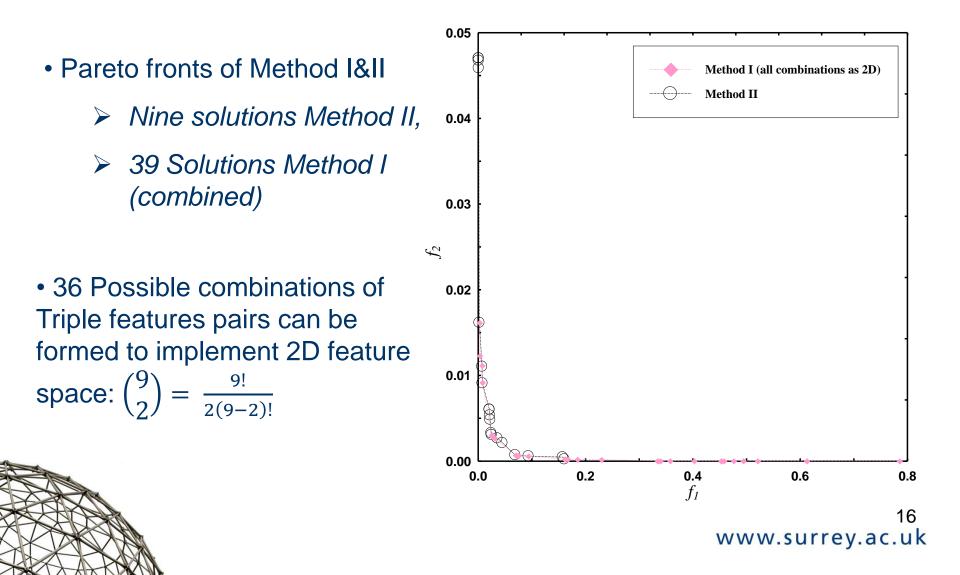










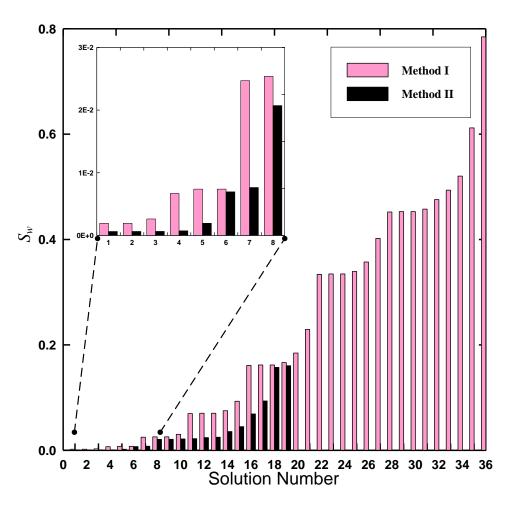






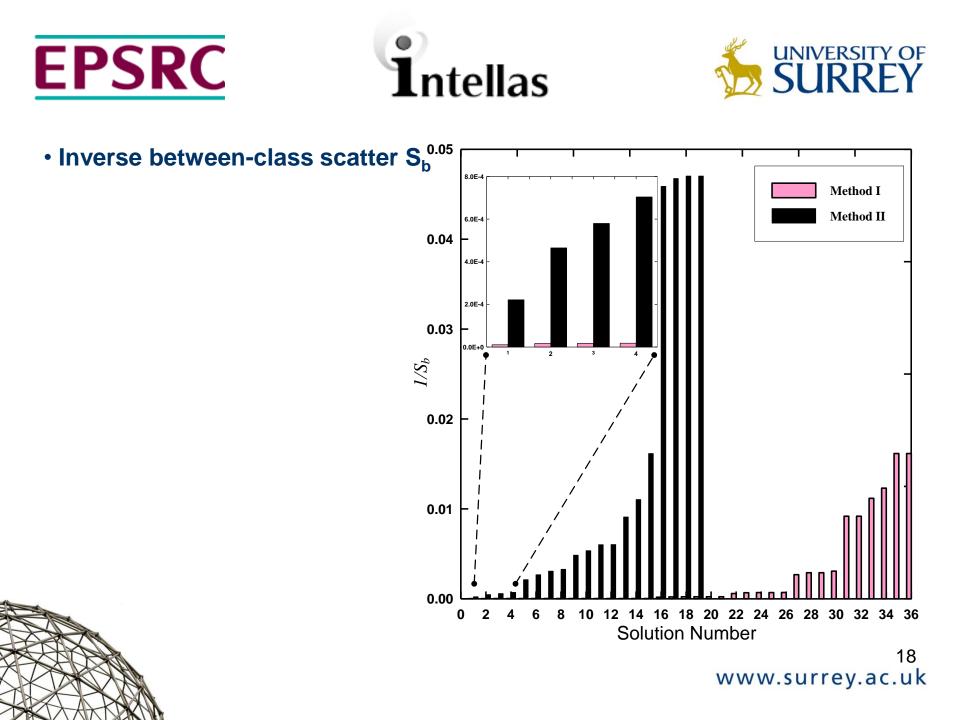


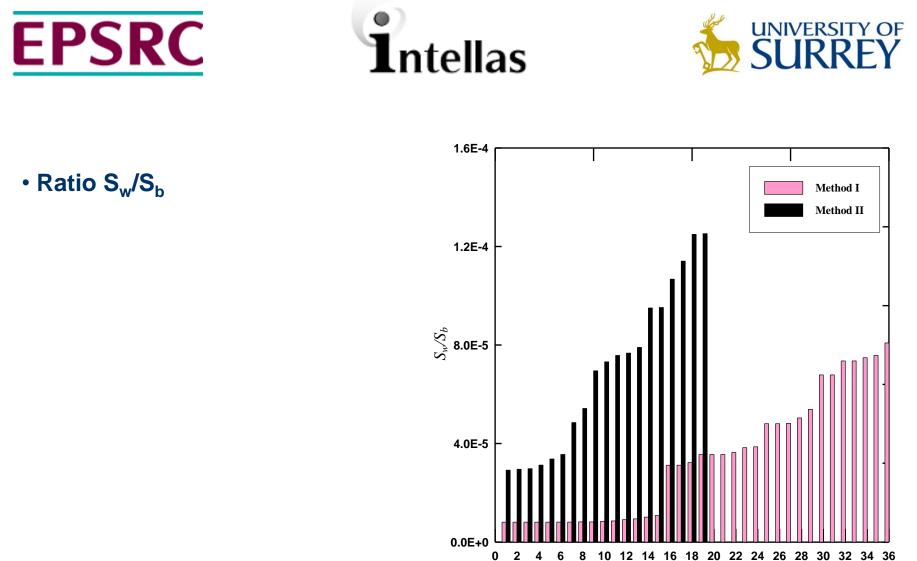
• Within-class scatter S_w











0

4 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 6 Solution Number



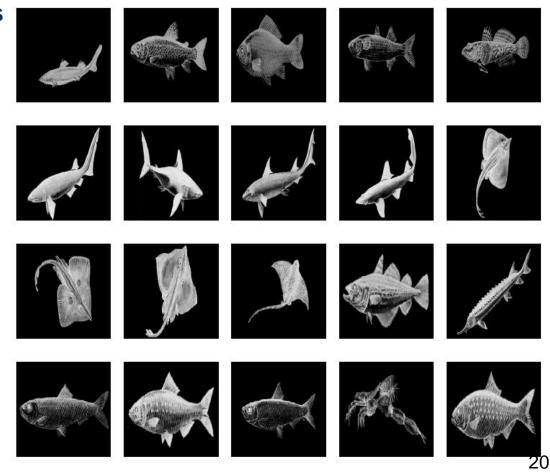




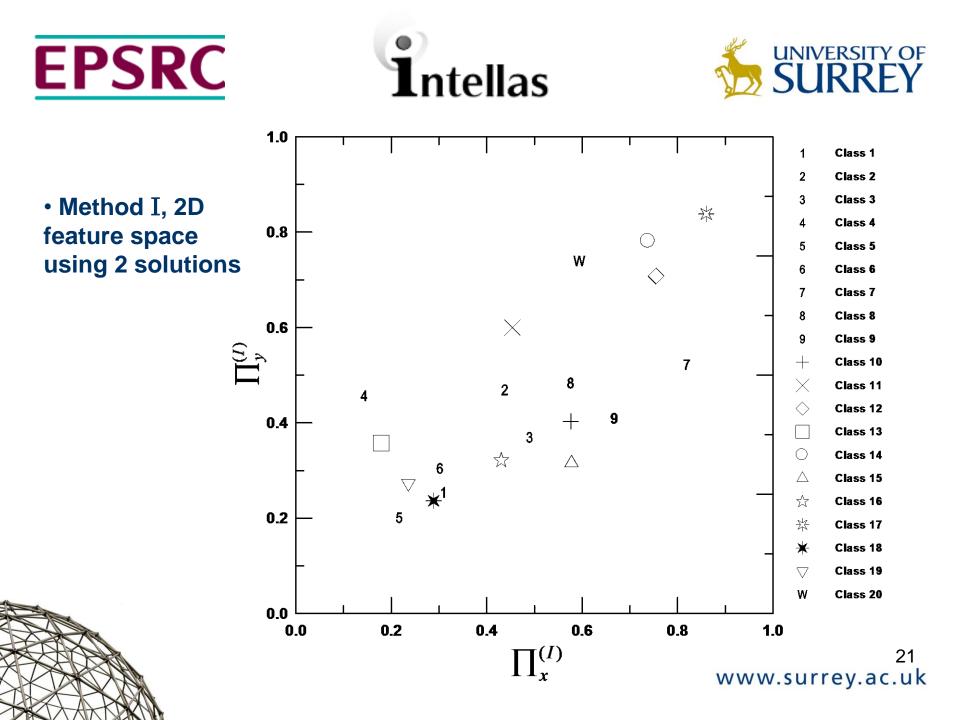
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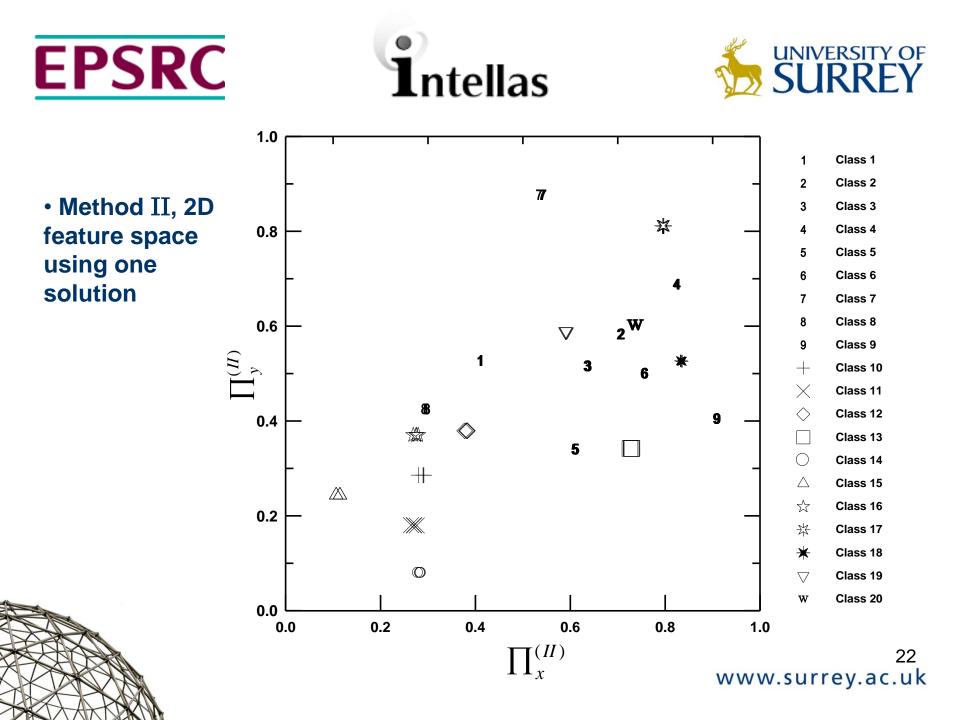
Fish Images database

- 20 class of 256x256 images
- 4 samples per class















Conclusion

• Two methods of Evolutionary Trace transform are developed for robust image feature extraction: Method I and Method II.

• Features from Method I represent a 1D feature space and can be combined with another solution to form a pair of features in 2D space. Whereas features from Method II can form a 2D space directly. Therefore, Method II take longer time to build non dominated solutions.

• While both methods evolved by using a few resolution (64x64) images, both methods show a comparative results in higher resolution and different images.

• Few solutions from both methods were explored and evaluated on a relatively large image database of **8554** images. While, Method I appears to provide better classification accuracy and take less time to evolve, Method II shows slightly less accuracy percentage. A fair comparison would be good if an average of more solutions are considered from both methods.

Future Work:

• Multiple solutions can be used with separate classifiers to build Heterogeneous Ensembles that could enhance performance further.

•Combined deformations (such as rotation + scale) and noise on test images would be practical to evaluate the two methods further. Complexity analysis on each solution should also be considered for fine tuning the algorithm.

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Thank you for your attention!

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