



# Improved Clustering and Soft Computing Algorithms

by

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# Abstract

Clustering algorithms have been widely applied and different approaches have been developed for different domains of application. This thesis investigates efficient and effective clustering and soft computing algorithms. In the investigation of  $k$ -medoids algorithms, several improved algorithms are proposed, such as the *Clustering Large Applications Based on Simulated Annealing (CLASA)* algorithm, the *Multi-Centroids with Multi-Runs Sampling Scheme (MCMRS)* and *Incremental Multi-Centroid, Multi-Run Sampling Scheme (IMCMRS)* algorithms. The *Partial Distance Search (PDS)*, *Triangular Inequality Elimination (TIE)* and *Previous Medoid Index* are also presented to improve the clustering speed of  $k$ -medoids based algorithms. In addition, a new memory utilization scheme is derived and applied to efficient  $k$ -medoids algorithms.

In the investigation of centroid-based clustering algorithms, the tabu search with simulated annealing algorithm is proposed and applied to codebook design for vector quantization. Genetic clustering is also presented for mean-residual vector quantization. Several theorems based on Hadamard Transform for nearest neighbour search are presented and applied to efficient cluster (codeword) search for vector quantization. A label bisecting clustering algorithm is proposed and applied to create a robust watermarking technique.

Parallel particle swarm optimization based on three communication strategies are proposed to solve the problems in which the relationship between parameters are either independent, loosely correlated, strongly correlated or unknown. Seven communication strategies for *Ant Colony Systems (ACS)* are proposed to improve the *ACS* for the traveller salesman problem and the *Constrained Ant Colony Optimization (CACO)* based on the quadratic metric, sum of  $k$  nearest neighbour distance, constrained addition of pheromone and a shrinking range strategy is also proposed and demonstrated to be better than the *Ant Colony Optimization with Different Favor (ACODF)*.

# Certification

I certify that this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

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Shu-Chuan Chu

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