Chapter 6

Conclusion and Future Work

This thesis aimed to answer the question - "can a Particle Swarm Optimiser be used to train a Support Vector Machine, and to what extent will it be successful?"

The research conducted for this thesis stood on two pillars. The first pillar was Support Vector Machines (SVMs) and algorithms to train them, and a decomposition-training algorithm was developed based on similar algorithms. The second pillar was Particle Swarm Optimisation (PSO), which is implemented as the optimisation method in the SVM training algorithm.

Concluding on the second pillar, it was shown that particle swarms can easily be used to optimise a function with equality constraints of the form $A\mathbf{x} = \mathbf{b}$. A variation of PSO, the "Linear Particle Swarm Optimiser" (LPSO), was introduced to optimise these types of problems, and conditions for the LPSO to be able to find any point in the feasible search space, was developed. There is a positive probability that LPSO can converge prematurely. The problem of LPSO's premature convergence was overcome by creating a "Converging LPSO" (CLSPO). A proof was given to show that CLPSO will at least converge to a local minimum. An important property of the two new PSO algorithms is that, if the whole swarm is initialised to lie within the hyperplane $A\mathbf{x} = \mathbf{b}$, then the swarm can optimise the objective function without having to worry about the set of constraints. This property was formally proved, and shows that LPSO and CLPSO are ideally suited to solving equality-constrained optimisation problems. The success of CLPSO (and premature convergence of LPSO) in optimising linearly constrained functions was experimentally illustrated. The experimental results were compared to results achieved with *Genocop II*, a genetic algorithm for constrained optimisation. Experimental results show a general similarity in convergence between *Genocop II* and CLPSO.

To conclude on the first pillar, it was shown that a PSO could be used to train a SVM. Some properties of CLPSO make it particularly useful to solve the SVM constrained quadratic programming problem, and it was used in the decomposition algorithm to solve the SVM's constrained subproblems. The CLPSO algorithm is simple to implement, and does not require any background of numerical methods. Accurate and scalable training results were shown on the MNIST dataset.

Although the CLPSO algorithm is simple, its speed in SVM training poses a practical bottleneck. Future research may include improvement to the speed of the algorithm by improving the CLPSO, and the cashing of kernel evaluations can be implemented.

Further research can also explore the possibility of parallel training of SVMs. Instead of selecting a single working set for optimisation, a number of working sets can be selected and optimised in parallel. If the working sets are distinct, the subproblems will be independent of each other, making this method a strong candidate for further investigation.

The standard methods of improving the original PSO can also be implemented on both LPSO and CLPSO. There is also scope for a proper analysis of CLPSO in the context of random search algorithms.

Finally, many interesting constrained problems are waiting to be solved!

Publications derived from this thesis

U. Paquet and A.P. Engelbrecht. "Training support vector machines with particle swarms," in *Proceedings of the International Joint Conference on Neural Networks*, Portland, Oregon, 2003.

U. Paquet and A.P. Engelbrecht. "Particle swarms for equality-constrained optimization," submitted to *IEEE Transactions on Evolutionary Computation.*

U. Paquet and A.P. Engelbrecht. "A new particle swarm optimizer for linearly constrained optimization," submitted to *The Congress on Evolutionary Computation*, Canberra, Australia, 2003.