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# Optimisation Algorithms for Hand Posture Estimation

 Springer

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*To our parents*

# Preface

Hand posture estimation is one of the main phases of hand gesture estimation. It refers to the process of estimating a real hand image obtained from an acquisition device in a computer. The accuracy of the estimated hand model has a direct impact on feature selection and classification. The current hand posture estimation techniques are divided into three classes: generative, discriminative and hybrid methods.

In the first, a model of the hand is generated and improved to model a hand in a computer accurately. In the second class, a database of different hand images is created and used to estimate the hand model. Finally, hybrid models use both discriminative and generative methods most sequentially.

This book first reviews the literature of hand posture estimation using generative methods and identifies the current gaps. The gaps are sensitivity to hand shapes, sensitivity to a good initial posture, difficult hand posture recovery in case of loss in tracking and lack of addressing multiple objectives to maximise accuracy and minimise computational cost.

To fill the gaps identified, a new hand model is proposed combining the best features of the current 3D hand models in the literature. Therefore, the first contribution of this book is the proposal of a new 3D hand model with simple shapes and low computational complexity to render. After the proposal of the 3D hand model, it is employed to develop a hand shape optimisation technique as the second contribution. The problem is formulated as a single-objective problem with several variables and constraints.

To find the global optimum for the single-objective problem formulated, particle swarm optimisation (PSO) is improved and used, as one of the most well-regarded optimisation algorithms in the literature with successful application in both science and industry. This book also demonstrates the effectiveness of the improved PSO in hand posture recovery in case of tracking loss.

The last contribution of this book is the formulation of the hand posture estimation as a bi-objective problem for the first time in the literature. The objectives identified and used are to minimise the error (maximise accuracy) and minimise the number of points in the point cloud, thus reducing the computational cost. After

formulating the problem, multi-objective particle swarm optimisation (MOPSO) is employed to estimate the Pareto optimal front as the solution to this bi-objective problem.

Both PSO and MOPSO were improved since it was observed that these algorithms are not very efficient for estimating hand postures. Therefore, their performance was improved using an evolutionary operator called evolutionary population dynamics (EPD). The performance of both techniques was tested on test functions and then applied to the problems mentioned in the preceding paragraphs.

The case studies in this book are 50 hand postures extracted from five standard data sets in the literature. All the case studies were employed to benchmark the proposed 3D hand model, hand shape optimisation and hand posture recovery. In the multi-objective section, the same case studies were used.

The results show that firstly, the proposed hand model is able to outperform the current hand models due to the better configuration and more uniform point cloud that it offers. Secondly, the proposed hand shape optimisation can find an optimal shape for different hand sizes and promote hand personalisation. Thirdly, the improved PSO is able to not only find an optimal shape for the 3D hand model but also recover from a wrong posture or tracking loss. Finally, this book shows that the improved MOPSO can readily estimate the Pareto optimal front for the bi-objective problem. This book also considers analysing the high-dimensional results of multi-objective optimisation using parallel coordinates to understand the relationship between the parameters and objectives of this problem for the first time in the literature.

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# Acronyms

DE	Differential evolution
DOF	Degree of freedom
EPD	Evolutionary population dynamics
GA	Genetic algorithm
GBEST	Global best in PSO
IGD	Inverted generational distance
IK	Inverse kinematic
MOEA/D	Multi-objective evolutionary algorithm based on decomposition
MOPSO	Multi-objective particle swarm optimisation
MS	Maximum spread
NN	Neural network
NSGA-II	Non-dominated sorting genetic algorithm version II
PBEST	Personal best in PSO
PCA	Principal component analysis
PSO	Particle swarm optimisation
PSO+EPD	PSO with evolutionary population dynamics
SP	Metric of spacing