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Appendices

Appendix A
List of Abbreviations

ATR	Automatic Target Recognition
atu	addition time unit
DWT	Discrete Wavelet Transforms
ECOC	Error Correcting Output Codes
FEC	Forward Error Correcting Codes
GCC	Generalized Code Concatenation
ISLE	Important Sampled Learning Ensemble
LDB	Local Discriminant Bases
LDFE	Local Discriminant Frame Expansions
LS	Least Squares
MCMC	Markov Chain Monte Carlo
MD	Multiple Description
MDC	Multiple Description Coding
MCS	Multiple Classifier Systems
MSB	Most Discriminant Bases
SAR	Synthetic Aperture Radar

Appendix B
Numerical Computations

This appendix presents the numerical computations concerning with all the algorithms listed in this dissertation. the numerical computation of the algorithms is calculated in term of *addition time units*, where 1 addition time unit (atu) is the time required to perform one addition. Based on a micro-processor based artificial neural networks [110], we assume that the execution of a comparison operation to be equal to 1 atu, the execution time of multiplication to be equal to 2 atus, and the time required for nonlinear function to be 2 atus.

The Computational Complexity of Neural networks [110]

For a conventional backpropagation neural networks utilizing the gradient algorithms, the computation in one iteration per sample of two-hidden-layer networks consists of

∘ $3H_1H_2 + 2H_1M + 3H_2N + H_1 + H_2 + 2N$ additions,

∘ $3H_1H_2 + 2H_1M + H_1N + 2H_2N + H_1 + H_2$ multiplications,

∘ and $H_1 + H_2$ sigmoid function computations,

where H_1, and H_2 are the numbers of the nodes in the first and the second hidden layers, respectively. M denotes the dimension of the input data, and N is the number of nodes of the output layer.

The Computational Complexity of Local discriminant bases

In computing local discriminant bases (LDB), we require to compute the local discriminant bases with respect to the discrete wavelet transform computation framework [57, 60]. This computation is summarized as follows:

∘ $2 \cdot (L-1)(\frac{M}{2^J}\log\frac{M}{2^J}) + (\frac{M}{2^J}-1)\log(\frac{M}{2^J}-1) + 1$ additions,

∘ $2 \cdot L(\frac{M}{2^J}\log\frac{M}{2^J}) + \frac{M}{2^J}\log\frac{M}{2^J} + 2^J + 2 \cdot 2^J$ multiplications,

∘ 2^J log function computations,

∘ and 2^J comparisons,

where L is the analysis filter length, and M is the dimension of the input data before transform. J denotes the highest resolution level of the local discriminant bases (LDB) tree.

The Computational Complexity of Local discriminant Bases Neural Network Ensembles

For Local discriminant Bases Neural Network Ensembles (LDBNNE) system, M_k becomes the k^{th} numbers of pixels obtained as the resolution-specific subband using for training the k^{th} classifier in the ensemble. Specifically, K networks are trained using the K resolution-specific subbands. As a consequence, the computation in one iteration per sample is the same as the conventional backpropagation before, but with much fewer weight connections.

It is well-known that in gradient-based neural network algorithms, the eigenvalue spread, $\lambda_{\max}/\lambda_{\min}$, is approximately proportional to the time-constant for the square error convergence and its effects on the performance [29, 106]. In fact, the convergence rate of the training objective function of neural networks will be much faster, when the eigenvalue spread of the input correlation matrix is much smoother [29].

In fact, the eigenvalue spread of the input correlation matrix for a critically decimated one dimensional signal system [56] has become smoother, if the input power spectral of the input data is well-behaved. This way, the training objective function are more likely smoother when we apply LDBNNE to a classification problem, which will lead us to better convergence speed.

Appendix C
Publications and Presentations

Widhyakorn Asdornwised and Somchai Jitapunkul,

"Multiple Description Pattern Analysis: Robustness to Misclassification using Local Discriminant Frame Expansions," To be published in IEICE Trans. Inf. & Syst., Oct. 2005.

Widhyakorn Asdornwised and Somchai Jitapunkul,

"Code Concatenation Based Multiple Classifier Systems for Automatic Target Recognition," Proc. of SPIE, Vol. 5433, pp. 41–52, Orlando, Florida, USA, 12-17 April 2004.

Widhyakorn Asdornwised and Somchai Jitapunkul,

"Multiple Description Coding Models/Multiple Description Sampling Based Multiple Classifier Systems and Its Applications to Automatic Target Recognition," Proc. of SPIE, Vol. 5439, pp. 210–221, Orlando, Florida, USA, 12-17 April 2004.

Widhyakorn Asdornwised and Somchai Jitapunkul,

"Automatic Target Recognition using Multiple Description Coding Models for Multiple Classifier Systems," In: Windeatt, T.; Roli, F. (Eds.): Multiple Classifier Systems. Lecture Notes in Computer Science, Vol. 2709, Springer-Verlag, Berlin Heidelberg New York, pp. 336–345, 2003.

Widhyakorn Asdornwised and Somchai Jitapunkul,

"Multiresolution–Based Committees of Networks: A Bayesian Point of View," IEEE ICIT '02. 2002 IEEE International Conference on Industrial Technology, Vol. 1, pp. 643–648, 2002.

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"Babilearn: An Incremental Learning Approach to Neural Network Design," ISC-IT '02, 2002 International Symposium Communications and Information Technology, pp. 487–490, 2002.

Vitae

Widhyakorn Asdornwised received the B.Eng. and M.Eng. degrees in Electrical Engineering from Department of Electrical Engineering, Kasetsart University, Thailand, and Chulalongkorn University, Thailand in 1984 and 1989, respectively. He also received the M.Sc. (in EE) degree from Department of Electrical and Computer Engineering, Drexel University, Philadelphia, USA in 1999. He is currently a full-time Lecturer at the Department of Electrical Engineering, Chulalongkorn University, Thailand. His research interests include Multiple Classifier Systems, Invariant Pattern Recognition, Image Compression, and Wavelet Applications.