



Gorn Tepvorachai

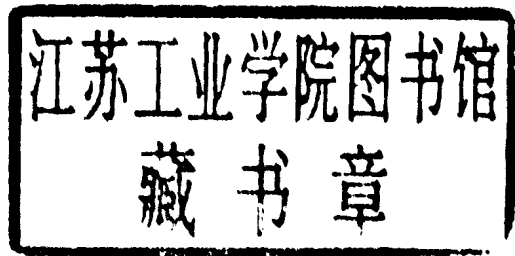
Evolutionary Platform for Retargetable Image Processing Applications

from Theoretical Neural Networks
to Real-Time Applications

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Chapter 1

Introduction

1.1 Overview

Current information computing systems can be characterized as static in nature. They rely on fixed architectures and specific software optimizations [2]. Today's computing systems were developed for fixed mission scenarios and can not provide effective information processing capability to support retargetable mission applications. They are not able to accommodate growing past experience on dynamic collaborative information centric strategies. The lack of versatility to dynamic mission requirements results in reduced performance or poorly matched processing of the application. A unique processing design for each specific mission sensor configuration cannot be afforded due to the required cost for multiple platforms and the inability to accurately define and predict mission variations before the deployment.

The majority of the existing works are focused on specific evolutionary system components, indirectly investigating possible system integration. For example, the IBM research center has developed a cellular computing architecture [3] for dual/quad core computer processor. This work is concentrated on reconfigurable architectures, which can potentially be the platform of choice for information processing and evolutionary system. Various algorithms and technologies rely on stochastic modeling of evolutionary techniques [4, 5, 6, 7] for some possibility that an innovative design will emerge. Their approaches do not guarantee the emergence of a novel design or easily reproduction of the design at a later time.

In this work, we propose a cognitive information processing (cognitive processing) on an evolutionary platform for retargetable applications. The main contributors of this work

are the cognitive processing (neural net ensembles) and the evolutionary platform (evolutionary training scheme). Our model considers multiple sensory information and generates the best cognitive recall from the memory. The proposed cognitive processing has been demonstrated in facial image recognition, image feature extraction, evolvable filter and other applications [8, 9, 10, 11, 12].

1.2 Motivation

An evolutionary system can be viewed as a system which has an ability to change its behavior to comply with its environment (external stimuli). It can re-organize its functionalities and structures with respect to external stimuli without human operators. A wide spectrum of engineering applications is presented and particular attention is paid to automated mission accomplishment problem areas that can be found in many engineering applications. Some applications for automated mission accomplishment are intended for deployment in remote sites, harsh terrain for human exploration, or lack of human assistance, such as an unmanned vehicle aircraft, a deep space explorer, or a surveillance camera/video unit. The evolutionary system has potential benefits on a remote site robot or in harsh environment, such as a deep space satellite, an unmanned aviation device, or a deep sea explorer. Instead of risking human lives on the high risk environment or requiring human resource, evolutionary systems can perform similar routine tasks. Other problems in these areas include image feature extraction, evolvable filter, preference learner, collaborative data, space explorer, and associative memory.

However, the evolutionary system needs to be well-trained and specific mission directed. This support is in the form of the provision of relevant information not only pertaining to an identified optimal solution for a specific condition but also to various characteristics of the system behavior. For instance, extracted information may relate to parameter sensitivity, degree of constraint satisfaction and multi-objective considerations. Whenever the target application mission objective changes, evolutionary system should be able to develop a mechanism to switch its surviving strategies. The mechanism can both increase performance while highlighting shortfalls of the mathematical models describing the system behavior under design.

Sometimes remote access communications between the device and the base control are limited. This proposed cognitive information processing system (cognitive processing) on