Inquiry: Robust Facial Recognition with Reconfigurable Platforms

Andrew Kruzner, Jack Merwin, Derek Rollend,
Ananth Nallamuthu, Chirag Gupta, and Melissa C. Smith
Clemson University, Department of Electrical and Computer Engineering
{akruzne, jmerwin, drollen, anallam, cgupta, smithmc} @clemson.edu

Abstract

Reconfigurable computing with Field Programmable Gate Arrays (FPGAs) has demonstrated performance advantages over microprocessor-based systems for many applications. FPGA-based computing systems are well suited to run multiple step algorithms, simulations, and other types of data intensive processing applications. One potential application yet to be fully explored on these architectures is biometrics, or human feature recognition algorithms. The use of reconfigurable computers in facial, iris, and finger/handprint matching situations could dramatically increase the speed, efficiency, and even accuracy of biometric algorithm processing. Our research focuses on the implementation of simultaneous algorithms (to cover multiple situational anomalies) coupled with a decision-making algorithm in the final stage to govern the overall identification matching.

1. Introduction

Biometrics is the use of physical features to identify a person. Immigration departments, gate entry control, ATMs etc. have already begun using biometrics for authenticating a person's identity. These applications of biometrics however are limited by situational conditions, false identifications, and system performance. There are many identification algorithms available but not all work well under all conditions for all subjects. With advancements in both algorithm coverage and processing technology to enable real-time, consistent, and robust identification, biometrics will find many new applications.

FPGA-based or reconfigurable computing provides hardware configurability for specific algorithms and tasks with advantages in speed, power, and footprint, making them more efficient than conventional processing architectures. The many degrees of parallelism available in FPGA-based systems also make them a powerful architecture for exploiting concurrency in algorithms. Reconfigurable computing systems are also capable of processing multiple algorithms in parallel and are especially well suited for applications where multiple algorithms utilized the same data set in parallel.

2. Background

Table 1 compares the most commonly used features for identification: fingerprint, iris and face [1]. The *low*, *medium*, and *high* ratings represent the applicability, robustness, reliability and performance of the different biometric techniques. For example, biometric identification via facial recognition provides high universality with low probability of

Table 1 Identification Features

Biometric	Universality	Uniqueness	Permanence	Collectability	Performance	Acceptability	Circumvention
Face	High	Low	Medium	High	Low	High	Low
Fingerprint	Medium	High	High	Medium	High	Medium	High
Iris	High	High	High	Medium	High	Low	High

circumvention but with low levels of performance and uniqueness. Similarly, fingerprint identification is highly unique and is typically a high performance technique but the openness to circumvention is also high. Moreover, facial recognition is very useful in public places where non-intrusive fingerprint and iris impressions are unavailable.

Facial recognition techniques rely on the facial features of a person to establish identity. The image of a person is compared with an existing database of known identities concentrating on the extracted facial features like eyes, lips, nose etc. Prior to any processing with a recognition algorithm, the image must be pre-processed into its mathematical representation. Preprocessing may also include image normalization steps to eliminate variations due to facial hair [16], illumination, posture, expression, scale etc., and thereby aid the recognition process.

In a typical recognition process, the training images and candidate image are projected onto a subspace such as Eigenspace or Fisher space based on some basis function. Then, with a facial recognition algorithm a comparison of the images is performed using measures such as the *L1* norm, *L2* norm, covariance, Mahalanobis distance, and correlation created by the Eigenvectors of the covariance matrix of the training data and the subspace created by the Fisher basis vectors of the data [2]. The final decision is made using a classifying algorithm like Bayesian classification, AdaBoost or Support Vector Machine [3]. The selection of a specific subspace depends greatly on the situation where the recognition is to be done. Furthermore, variations within the subspace also effect performance. For example, the selection of vectors to create the subspace and measures to decide which images are a closest match, both effect performance due to the complexity and number of resulting computations. Moreover, the classifying algorithm selection also effects the final result.

As shown in Table 1, though the facial recognition technique is better than fingerprint and iris based recognition techniques in terms of collectability and acceptability, facial recognition techniques are not yet commonly used due to the low performance of the algorithms and lower uniqueness.

The low performance of the facial recognition algorithms is due to the fact that different facial images of the same person may easily differ due to variations in illumination conditions, facial hair, facial expressions, temporal changes, ageing factors in the face, etc., leading to increased computing complexity and lower recognition accuracy [4]. The facial recognition algorithm used should be able to identify matches even when the compared images differ in such attributes. Though a number of facial recognition algorithms are available, none of them is robust enough for use with all types of input data [5]. A consensus made by comparing the results of multiple algorithms could improve the reliability of the facial recognition system. But processing data through multiple algorithms sequentially would be very slow. Hence there is a need for a computing architecture that would enable parallel processing of multiple algorithms in a small, low-power footprint for embedded applications and in real-time (or pseudo) performance for timely identification.

FPGA-based systems are emerging as an alternative to microprocessors for several classes of applications [6]. Their lower clock speeds keep power consumption low and performance is maintained with application specific hardware implementation. Via runtime reconfiguration, multiple algorithms can be implemented in FPGA during different segments of the runtime thereby supporting the overall application. FPGAs have previously been used to accelerate biomolecular simulations [7] by implementing computational bottlenecks in the reconfigurable hardware. Alternatively, several algorithms (either homogeneous copies of a single algorithm working on different data or heterogeneous algorithms working on the same data) can be implemented to run in parallel on the FPGA as demonstrated by several large-scale data manipulation applications such as encryption [8], and string pattern matching [9].

The MISD capability of FPGAs will be exploited to process the same input data with a heterogeneous set of algorithms simultaneously. This capability will enable real-time comparison of algorithm results and when coupled with a final decision algorithm, a more robust identification.

3. Implementation

The goal of this research is to use the capabilities of reconfigurable computing platforms to implement multiple facial recognition algorithms in parallel and shown in Figure 1. In depth performance analysis of each selected facial recognition algorithm will reveal which part of execution will be improved the most by reconfigurable logic. Once the critical computations of the algorithms have been identified the next step is to implement these different algorithms in parallel on the same system, thereby producing results from multiple algorithms in parallel for each recognition task. A final level decision algorithm will be developed that receives the result of each algorithm and determines the most accurate identification match.

There are currently many facial recognition algorithms available. The range of complexity of these algorithms is very wide, but some are easier to implement than others. Initially, the focus will be on several algorithms that are regarded as the standard against which all others facial recognition algorithms are compared: Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA). These algorithms are some of the oldest and most efficient facial recognition algorithms. Once the system is fully implemented with this initial set of algorithms, experimental results and analysis will determine if other algorithms will be required. Potential algorithms for future implementation include Elastic Bunch Graph Mapping (EBGM), Hidden Markov Models, and the Bayesian Intrapersonal/ Extrapersonal Classifier (BIC) [10-12].

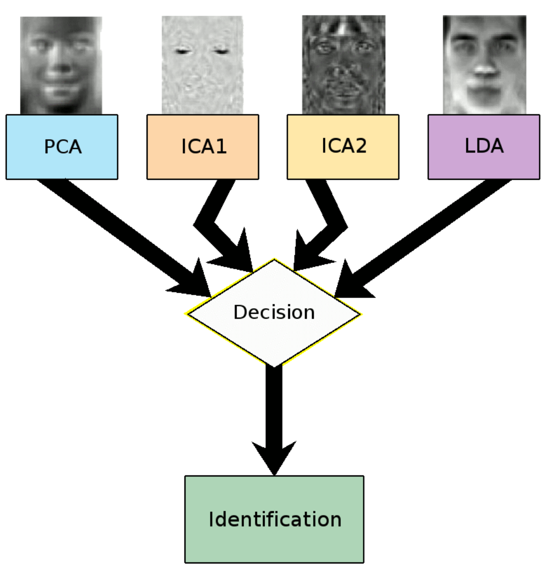

Figure 1 Parallel Algorithm for Identification

One of the oldest and most efficient algorithms for performing face recognition is the PCA based Eigen face construction [13]. In this algorithm the test images are stored in the form of Eigenvectors. Each Eigenvector corresponds to a face image. Faces are represented by their projection onto a subset of Eigenvectors. So each image in the database is represented as point in *M*-dimensional face space where *M* is the number of training images. A similar type of approach is used for the ICA and LDA based face recognition. The PCA algorithm decorrelates the input data using second-order statistics and thereby generates compressed data with minimum mean-squared reprojection error. Research has shown that a substantial amount of information is contained in the higher order relationship between the pixels of face images, hence, ICA minimizes both second-order and higher-order dependencies in the input. ICA can be implemented using two architectures viz ICA1 and ICA2. ICA1 treats the images as random variables where pixels are the outcome; ICA2 treats pixels as random variables where images are the outcome [14]. Finally, the LDA-based face recognition is similar to PCA, but in LDA the Eigenvalues are calculated using a separation matrix rather than a covariance matrix [15].

The benefits of implementing these compute intensive algorithms with FPGA-based systems include the potential power, space, and cost savings vs. traditional CPUs. As mentioned earlier, FPGAs are also inherently parallel and can be configured for optimum performance of a specific algorithm. These features will be exploited to implement multiple facial recognition algorithms in parallel and provide analysis results from multiple recognition algorithms simultaneously. Further, this implementation architecture will enable the use of facial recognition techniques in area previously limited by algorithm performance.

4. Conclusions and Future Work

This paper presents our analysis of biometric identification techniques and their suitability for reconfigurable computing. Current algorithms and techniques suffer from one or more issues related to performance, robustness, reliability, and circumvention. We are investigating the use of multiple techniques or algorithms implemented in parallel on FPGAs as a means to improve these issues. Our initial analysis suggests that a set of algorithms together with a final level decision algorithm can provide a robust and reliable identification. Further, we expect the implementation in reconfigurable hardware will improve the facial recognition algorithm compute speed.

The challenges and questions under investigation by the undergraduate creative inquiry team at Clemson University are development of the final level decision algorithm, composition of the algorithm set (balancing the complexity of the algorithm with its contribution to final identification decision), implementation of one or more algorithms on an FPGA, and exploiting parallelism in the algorithms. Detailed analysis of the chosen algorithms will attempt to exploit any common computations, if they exist, across the algorithms and share logic or intermediate results during implementation. Finally, experimental analysis and performance studies will be conducted to develop a robust decision algorithm for use with the parallel implementation.

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