A PREDICTIVE FUNCTION OPTIMIZATION ALGORITHM FOR MULTI-SPECTRAL SKIN LESION ASSESSMENT

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ABSTRACT

The newly introduced Kubelka-Munk Genetic Algorithm (KMGA) is a promising technique used in the assessment of skin lesions. Unfortunately, this method is computationally expensive due to its function inverting process. In the work of this paper, we design a Predictive Function Optimization Algorithm in order to improve the efficiency of KMGA by speeding up its convergence rate. Using this approach, a High-Convergence-Rate KMGA (HCR-KMGA) is implemented onto multi-core processors and FPGA devices respectively. Furthermore, the implementations are optimized using parallel computing techniques. Intensive experiments demonstrate that HCR-KMGA can effectively accelerate KMGA method, while improving its assessment accuracy as well.

Index Terms— Multi-spectral Image Processing, Light-Tissue Interaction, Genetic Algorithm, Kubelka-Munk model, Embedded System, SW/HW Co-design, FPGA, High-Level Synthesis, High-Performance Computing, POSIX Thread

1. INTRODUCTION

Usually, well trained dermatologists analyze the skin color and interpret clinical pathologies depending on their knowledge and experience, which often results in the mistakes due to subjective judgment. Recently, in order to make the diagnosis conclusions objective, computer assisted methods for cutaneous lesions assessment increasingly attracts medical researchers. More precisely, some image processing systems are used to minimize the usages of the naked eyes and quantify more accurately the lesion zone's optical properties.

The earlier image acquisition devices are normal color cameras that can only acquire visible light's color information. Meanwhile, it is found that invisible light carries much more important information than the former. In order to produce an enhanced information for diagnostic, some novel sophisticated multi-spectral imaging devices and processing methods emerged. To our knowledge, two approaches are usually used to analyse human skin reflectance spectrum. The first is based on statistical analysis of the reflectance spectrum, such as partial least squares regressions [1], Support Vector Machine (SVM) [2], Blind Source Separation (BSS) [3] or Independent Component Analysis (ICA) and Principal Component Analysis (PCA) [4]. These techniques assume that skin reflectance is a combination of different source components' spectra weighted by their mixing quantities. The second is the analysis of the reflectance spectra by means of physical models of light transportation based on the optical properties of skin (scattering and absorption). Based on the modified Beer-Lambert law or Monte-Carlo simulations, different light propagation models have been developed. The properties of the model can be obtained from available *a-priori* knowledge of the skin absorption spectra and scattering properties. Thus, compared with the statistical analysis of the reflectance spectrum, this approach is not affected when the skin composition is different from the composition assumption.

Using the knowledge of the skin absorption and scattering properties, a novel multi-spectral skin lesion assessment method, Kubelka-Munk Genetic Algorithm (KMGA), is proposed by Jolivot et al. in [5]. This method combines the Kubelka-Munk (KM) model [6] with Genetic Algorithm (GA) for the optimization process. It can analyze both of the most important light absorbers (blood and melanin) in the skin according to the multi-spectral images which is acquired only by a hand-held multi-spectral camera. However, its initial prototype is very time consuming due to the low convergence rate of the evolution process. This shortcoming seriously hampers the practical application of this technology as an aid for cutaneous lesions diagnostics. So finding an efficient function optimization approach for such a skin lesion assessment method becomes a new challenge.

This paper focuses on the performance improvement of the KM based skin lesion assessment algorithm. We develop a novel High-Convergence-Rate KMGA using a predictive evolution strategy. Our introduced approach can effectively improve the performances of KMGA in terms of both accuracy and efficiency by speeding up its convergence rate. Furthermore, a series of optimizations are made to improve the code efficiency or reduce the hardware consumptions. In the experiments, we compare HCR-KMGA with KMGA using different hardware devices. The results indicate that

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our approach achieves higher performances both in terms of accuracy and efficiency.

The remainder of this paper is organized as follows: Section 2 specifies the Predictive Function Optimization Algorithm; Section 3 describes the optimizations method carried out on the prototype of HCR-KMGA and its implementation processes for different platforms; Section 4 analyzes the evaluation experiments; finally, a conclusion is given in Section 5.

2. FUNCTION OPTIMIZATION STRATEGY

Within the Light-Tissue Interaction based skin lesion assessment methods, the total reflectance of the incident light R_{tot} can be expressed as a function of the interested skin parameters with a fixed wavelength. For the KM model, it can be expressed as:

$$R_{tot} = f_{KM}(f_{mel}, D_{epi}, f_{blood}, C_{oxy}, D_{dermis}) \quad (1)$$

where f_{mel}, D_{epi}, f_{blood}, C_{oxy} and D_{dermis} refer respectively to the melanin concentration, epidermis thickness, volume blood fraction, oxygen saturation and dermis thickness. Equation (1) is a complex non-linear function with five arguments which is hard to inverse. KMGA optimizes this function according to a standard genetic algorithm. This optimization process is the search heuristic that mimics the process of natural selection. It generates solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. However, the evolution process of a pure natural-simulated genetic algorithm is time consuming, and can easily get trapped into a local optima. This is because GA always generates the new populations in a random way firstly, and then selects the best individual according to the fitness function. This enormously reduces the chance to find a better individual in the next iteration which results in a very low convergence rate. In order to improve the performances of the GA based designs, some researches improved the evolution process by using the predictive approaches [7, 8]. With the enlightenment of these efforts, we develop a Predictive Function Optimization Algorithm (PFOA) that can speed up the convergence rate of the evolution process by predicting the possible evolution directions.

Fig.1 illustrates the over-all architecture of PFOA. Like the conventional GA, the system first initializes randomly the population. However, in the evolution process, only best-individual selection process are kept, while crossover-mutation and random selection are replaced by predictive evolution and random evolution. After each iteration, the best individuals are directly copied from the last generation into the next one for the purpose of fast convergence. Meanwhile, some of the individuals evolve depending on a prediction strategy, which can greatly further speed up the convergence rate of population evolution. Finally, the rest of individuals

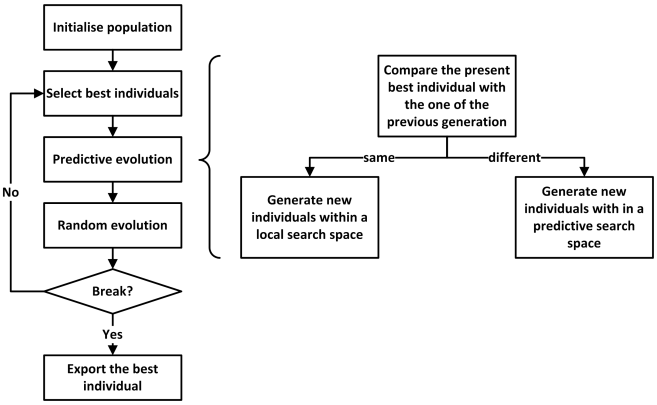

Fig. 1. Over-all architecture of PFOA

are re-performed randomly in order to reduce the possibility of falling down into a the local optima.

Depending on different fitness functions, designers can customize different prediction strategies. In KMGA, the population consists of a few hundred individuals, and in each iteration, several new genes are generated via crossover-mutation process. In order to accelerate the convergence speed of the algorithm, a prediction strategy that can reduce each iteration's search space by predicting the evolution direction is performed as shown in the right of Fig.1.

PFOA first compares the best individuals of the last two generations, and then takes different steps to adjust the search space. We base the prediction strategy on the assumption that higher parameter values had better fitness while $x_{n-1} > x_{n-2}$, and lower parameter values had better fitness while $x_{n-1} < x_{n-2}$ (see Fig.2-(a) and (b)). However, this method is effective only when the present individual is enough far away from the optima, otherwise a much smaller search space may be required to enable the algorithm to find a better individual with as few iterations as possible. Once that happens, the search space of the n^{th} iteration will be locked within the scope around x_{n-1} in order to enhance the chance of evolution as shown in Fig.2-(c).

Since the optimization function is unknown, it is impossible to always correctly predict the position of the global optima. But this mistake can be quickly corrected in the following iterations. For example, the predicting scope doesn't include the optima in Fig.2-(b), and within this scope no better individual can be found. However, this makes the algorithm restricts its search space around x_{n-1} in the following iterations, within which a new best individual can be easily found at the right of x_{n-1}.

It should also be noted that sometimes this method may as well lead the evolution downto a local optima. Thus, after prediction evolution, some random individuals are performed in order to avoid it. Unlike GA, PFOA completely regenerates all the individuals in a random way instead of crossovers or mutations. This method greatly enriches the sample types of

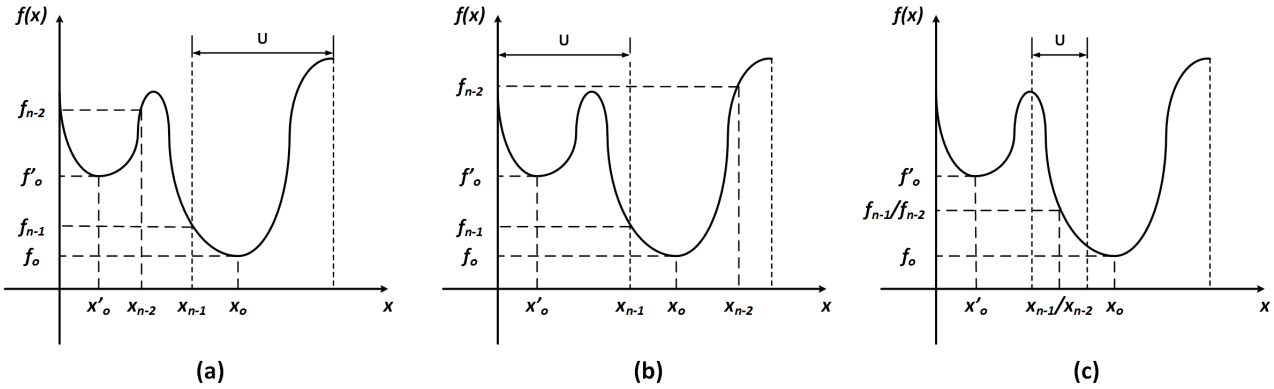

Fig. 2. Search space prediction of PFOA: U is the new search space, x_n and f_n are the parameter and fitness value of the n^{th} iteration's best individual, (x'_o, f'_o) is the local optima and (x_o, f_o) is the global optima of the optimization function.

genes, the risks of missing the optima is therefore reduced.

3. IMPLEMENTATION DESCRIPTION

We implement a High-Convergence-Rate KMGA (HCR-KMGA) by combining the KM model with the PFOA. Considering that the five skin parameters of KM have different effects on the final fitness, they should be independently analyzed. Thus, we applies PFOA to all of them respectively. That is, after the fitness comparison, the search space of each parameter is defined independently via the proposed prediction strategy. The algorithm is prototyped using C language and respectively implemented onto the multi-core CPUs and an FPGA device. Nevertheless, in order to improve the performances of the final implementations, three prototype optimizations are used, including KM function reducing, individual information optimization and terminating condition expending.

3.1. Prototype optimization

3.1.1. KM function reducing

According to our test, the population initialization and generation takes up to 96% of the total execution time in KMGA. In these process, KM is the key technique. Meanwhile, the mathematical expression of the KM model is complex. This results that the C symbolic expression of KM is quite inefficient to the compiler. Thus, we use a reduced KM model that is mathematically simplified in our previous work in order to reduce the unnecessary repetitive operations (see Section 3.1 of [9]). The computation cost of re-specified KM model is only 45.85% of its prototype.

3.1.2. Individual information optimization

The individuals of KMGA consist of the optical properties, the chemical properties and the fitness value. But it is well known that the optical properties are performed from the chemical properties via the KM model. That offers a nice opportunity to compress the data size of the individual information by removing out the data that could be computed immediately. We therefore perform the individual of our implementations by using only the chemical properties and fitness value. This optimization can greatly reduce the hardware consumption in terms of memory.

3.1.3. Terminating condition expending

The evolution process of Genetic Algorithm is terminated after a number of iterations according to the terminating conditions. A main issue that always affects the selection of terminating conditions is that: defining a condition easy to reach consumes fewer hardware resources but may reduce the accuracy performances of designs, while a hard condition may lead to extensive computational time, the algorithm can even be trapped into an infinite loop. Thus, instead of forcing the algorithm to end by setting a default iterating limitation, we expend the terminating conditions from a single to three independent ones, including max continuous invalid iteration level, fitness level and total-iteration level. This method can reduce the resource consumptions by avoiding the redundant iterations and prevent the evolution from trapping into an infinite loop as well.

3.2. Implementing flows

3.2.1. CPU

In order to efficiently use the resources of multi-core processors, we realize the CPU implementations within a POSIX multi-thread framework as shown in Fig.3. This method allows us to multiply the speed of the designs by simultaneously executing multiple threads depending on the available core number of the target processor. Considering that the processing of each pixel is independent, we cut the whole

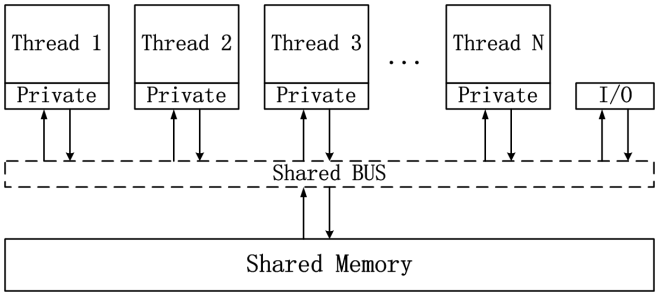

Fig. 3. POSIX thread framework.

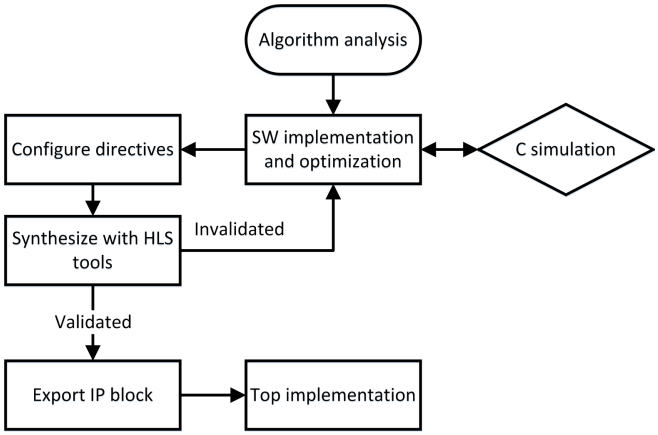

Fig. 4. Development process for the FPGA implementation.

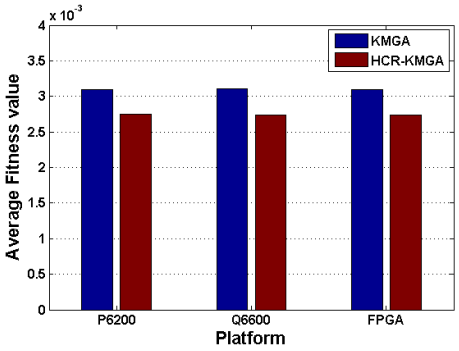

Fig. 5. Fitness comparison.

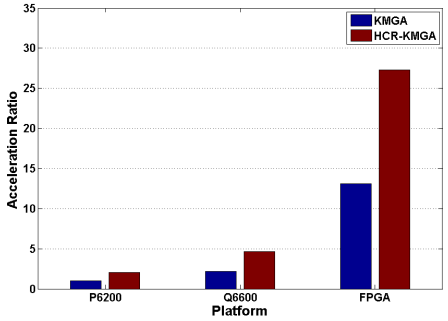

Fig. 6. Efficiency comparison.

lesion image into multiple zones and distribute them to the different threads. Since the local memory of the threads are usually quite small, we allocate the image information into the shared memory and manipulate the target data of each operation according to their address.

3.2.2. FPGA

The FPGA implementation of the desired algorithm is realized within a High-Level Synthesis (HLS) based SW/HW Co-design flow (see Fig.4). That is, we synthesize directly the prototype of HCR-KMGA from C into the textual description of a circuit diagram for FPGA devices [10]. In additional, for the purpose to maximize the execution speed of the system with the hardware constraints, the final implementation is optimized by directives configurations, including *function inline*, *loop unroll* and *array reshape*, etc [11]. But it should be noted that we only partly pipeline our designs in order to make the resource consumption available to the target device.

4. EXPERIMENT AND ANALYSIS

Section 4 evaluates HCR-KMGA by comparing it with the conventional KMGA proposed by Jolivot et al. [5, 12]. The dual core processor P6200, the quad core processor Q6600 and the Virtex7-XC7VX1140T of Xilinx are selected as the hardware platforms for an unbias comparison.

Fig.5 displays The average fitness values of our implementations. It indicates that all the HCR-KMGA implementations have lower fitness values than the KMGA ones. This demonstrates that PFOA performs better in terms of accuracy no matter which hardware platform is used. Meanwhile, it is also found that the fitness values of the FPGA and CPU implementations are almost identical. This is because the HLS based SW/HW Co-design framework that we followed can well transplant an algorithm specified in C onto the target device almost without any omissions of functions.

The efficiency performances of our implementations are compared in Fig.6. Thanks to the prediction evolution strategy, HCR-KMGA offers an average acceleration gain of $2.08\times$ relative to the implementations of KMGA. Nevertheless, the loop-level and instruction-level parallelism enable FPGAs to appear a much better hardware performances than CPUs, although it has a lower clock frequency. The average speed gains due to the platform are $13.21\times$ and $5.93\times$ for FPGA v.s. P6200 and FPGA-HCR-KMGA v.s. Q6600 respectively.

Finally, we compare the hardware resources consumption of the two FPGA implementations in Table 1. This comparison indicates that HCR-KMGA consumes much less RAM than KMGA. This is because the data size of individual are

Components	KMGA	HCR-KMGA
BRAM	192	32
DSP	2352	2431
FF	467264	493177
LUT	668784	712894

Table 1. Hardware consumption of FPGA implementations.

reduced according to the approach presented in Section 3.1.2, so there is no need to allocate as much storage space as before. In contrast, HCR-KMGA consumes more other components relative to KMGA. This is because PFOA has a more complex evolution process, HLS has to consume more resources for the operation control flow. However, this difference is very tiny, it can even be ignored in practical applications.

5. CONCLUSION

This paper presents a high-convergence-rate evolution algorithm for the Kubelka-Munk model based skin lesion assessment method. It can accelerate the function optimization process of the algorithm by predicting the convergence direction. In additional, we prototyped a HCR-KMGA according to the proposed algorithm using C language and implemented it onto the multi-core CPUs and FPGA devices for evaluation. Nevertheless, the target implementations are optimized using POSIX Threads framework and HLS based SW/HW Co-design flow. The experiments demonstrate that PFOA can effectively improve the performances of KMGA both in efficiency and accuracy. Furthermore, FPGA devices may achieve more acceleration gains for this design. We believe that the achievements of this work can bring rich enlightenment to the studies for computer assisted fast skin lesion assessment and accelerate the commercialization of KMGA method.

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