Advanced Branch Predictors for Soft Processors

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***Abstract*—The abstract goes here.**

I. Introduction

Field Programmable Gate Arrays (FPGAs) are increasingly popular to be used in embedded systems. Such designs often employ one or more embedded microprocessors, and there is a trend to migrate these microprocessors to the FPGA platform. Although these soft processors cannot match the performance of a hard processor, soft processors have the advantage that the designers can implement the exact number of processors to efficiently fit the application requirements.

Current commercial soft processors such as Altera's Nios II [1] and Xilinx's Microblaze [2] are in-order pipelines with five to six pipeline stages. These processors are often used for less computation-intensive applications, for instance, system control tasks. To support more compute-intensive applications, a key technique to improve performance is branch prediction. Branch prediction has been extensively studies, mostly in the context of application specific custom logic (ASIC) implementations. However, naïvely porting ASIC-based branch predictors to FPGAs results in slow and/or resource-inefficient implementations since the tradeoffs are different for reconfigurable logic. Wu et al. [3] have shown that a branch predictor design for soft processors should balance its prediction accuracy as well as the maximum operating frequency. They proposed an FPGA-friendly minimalistic branch prediction implementation *gRselect* for Altera's highest performing soft-processor Nios II-f.

Wu et al. limits the hardware budget of the gRselect predictor to one M9K Block RAM [4] on Altera Stratix IV devices, which is the same hardware budget as Nios II-f. Such a small hardware budget prohibits more elaborated and accurate branch prediction schemes such as perceptron [5] and TAGE [6]. This work looses the hardware budget constraint and investigates FPGA-friendly implementations of perceptron and TAGE predictors. This work also assumes a pipelined processor implementation representative of Altera's Nios II-f for comparison versus gRselect.

Specifically, this work makes the following contributions: (1) It studies the FPGA implementation of the perceptron predictor and TAGE predictor, including many optimizations to improve maximum frequency of these predictors. (2) It shows that comparing the branch direction prediction accuracy over the benchmarks versus gRselect, perceptron is $\tilde{1}\%$ worse while TAGE is $\tilde{1}\%$ better, assuming these predictors can be accessed in a single cycle. (3) It discovered that TAGE is too slow for single-cycle access, so in reality TAGE can only provide a prediction in two cycles. This work proposes an overriding predictor that uses a simple base predictor to provide a base prediction in the first cycle, then override that decision should TAGE disagree with the base predictor in the second cycle. It shows that the overriding TAGE predictor achieves 5.2% better instruction throughput over gRselect.

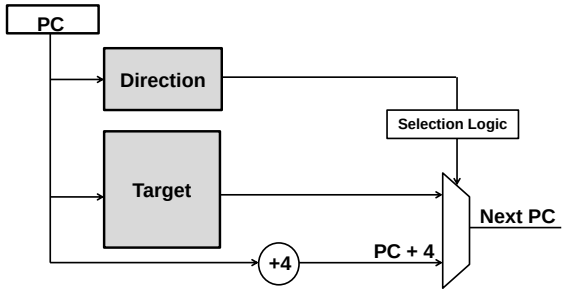

Fig. 1: Canonical Branch Predictor.

II. Background and Goals

Fig. 1 shows the organization of a typical branch predictor comprising a direction predictor and a target predictor. The predictor operates in the fetch stage where it aims to predict the program counter (PC), that is the address in memory, of the instruction to fetch in the next cycle using the current instruction's PC and other dynamically collected information. The direction predictor guesses whether the branch will be taken or not. The target predictor guesses the address for predicted as taken branches and function returns respectively. The multiplexer at the end selects based on the branch type and the direction prediction whether the target is the fall through address (PC+4 in Nios II) or the target predicted by the target predictor. Since, at this point in time, the actual instruction is not available in a typical ASIC implementation, it is not directly possible to determine whether the instruction is a return, a branch, or some other instruction. Accordingly, a Selection Logic block uses either pre-decode information or a PC-based, dynamically populated lookup table to guess which target is best to use. With the latter scheme, when no entry exists in the lookup table, some default action is taken until the first time a branch is encountered. Once the branch executes, its type is stored in the lookup table where it serves to identify the branch type on subsequent encounters. This scheme is not perfectly accurate due to aliasing.

A. Design Goals

This work aims to implement perceptron and TAGE that has high operating frequency as well as accuracy to maximize execution performance. As section III-B will show, a

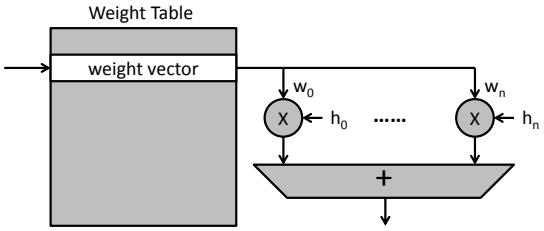

Fig. 2: The preceptron branch predictor.

single-cycle TAGE is prohibitively slow. Therefore, this work proposes an overriding TAGE predictor that produces a base prediction in one cycle and overrides that decision with a better prediction if the later prediction differs from the base prediction. Since perceptron and TAGE both requires large storage spaces, on-chip resources is not the main concern of this paper.

III. Branch Prediction Scheme

This section discusses the structure of the branch predictors considered, including perceptron and TAGE direction predictor and the target predictor. Sections III-A and III-B discusses perceptron and tage, while section III-C discusses the target predicor.

A. Perceptron Predictor

The perceptron predictor use vectors of weights (i.e., perceptrons) to represent correlations among branch instructions [5]. Fig. 2 shows the structure of a perceptron predictor.

When making a prediction, a weight vector is loaded from the table. Then, each weight is multiplied by 1 if the corresponding global branch history is taken, and by -1 otherwise. Finally, the products are summed up, the perceptron predicts taken if the sum is positive, and not taken otherwise.

B. Tagged Geometric History Length Branch Predictor (TAGE)

The TAGE predictor features a bimodal predictor as base predictor T_0 to provide a basic prediction and a set of M tagged predictor components T_i [6]. These tagged predictor components T_i, where $1 \leq i \leq M$, are indexed with hash functions of the branch address and the global branch/path history with various length. The global history lengths used for computing the indexing functions for tables T_i form a geometric series, i.e., $L(i) = (int)(\alpha^{i-1} \times L(1) + 0.5)$. TAGE achieves its high accuracy by utilizing very long history lengths.

Fig. 3 shows a 5-component TAGE predictor. Each table entry has a 3-bit saturating counter *ctr* for prediction result, a *tag*, and a 2-bit useful counter *u*. The indices of the tables are produced by hashing PC and global history with various lengths. A valid prediction result from each table is provided only on a tag match (i.e. a hit). The final prediction of TAGE comes from the hitting tagged predictor component that uses the longest history.

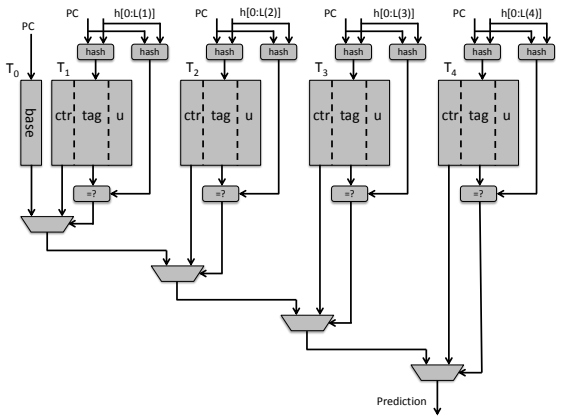

Fig. 3: A 5-component TAGE branch predictor.

C. Branch Target Predictor

Branch Target Prediction usually requires a Branch Target Buffer (BTB), a cache-like structure that records the addresses of the branches and the target addresses associated with them. If a branch is predicted to be taken and there is also a BTB hit, then the next PC is set to be the predicted target. A BTB can also have set-associativity to reduce the impact from aliasing.

Another common structure for branch target prediction is a Return Address Stack (RAS). It is a stack-like structure that accurately predicts the target address of function returns. When a call instruction executes, the return address of that call is pushed on RAS. When the processor executes the corresponding return instruction, RAS pop the return address and always provides the accurate prediction. Most modern processors have a shallow RAS because typical programs generally do not have very deep call depths. RAS will fail to provide correct target prediction if it is overflowed.

Wu et al. has shown that within the same hardware budget as Nios II-f (i.e., 1 M9K BRAM), eliminating the BTB and use *Full Address Calculation* (FAC) together with RAS results in better performance [3]. FAC is a technique that calculates the target address in fetch stage to accurately predict target addresses for direct branches, whose target can be calculated based on the instruction itself [1]. Wu et al. has shown that direct branches and returns consist of over 99.8% of all branches. Implementing FAC with RAS can cover these branches with 100% accuracy, therefore having a BTB to cover all branches results in negligible improvement in target prediction accuracy. On the other hand, eliminating the BTB and dedicate the entire BRAM for direction prediction improves direction prediction accuracy significantly.

Since we remove the hardware budget constraint in this work, adding a BTB for better target prediction coverage can improve target prediction accuracy. However, our simulations show that the accuracy of the branch predictor is still better without a BTB. This is because when the target predictor only has FAC and RAS, it never predicts indirect branches that are not returns because it is not capable to do so. As a result, the destructive aliasing in the **direction** predictor is alleviated because less branches are being predicted. Based on this observation, this work uses FAC with RAS as the branch target predictor, which is the same as gRselect.

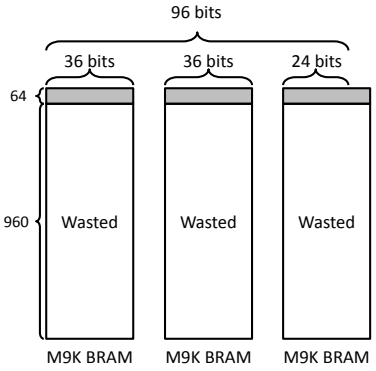

Fig. 4: Inefficiency using M9K BRAMs to implement wide but shallow perceptron tables.

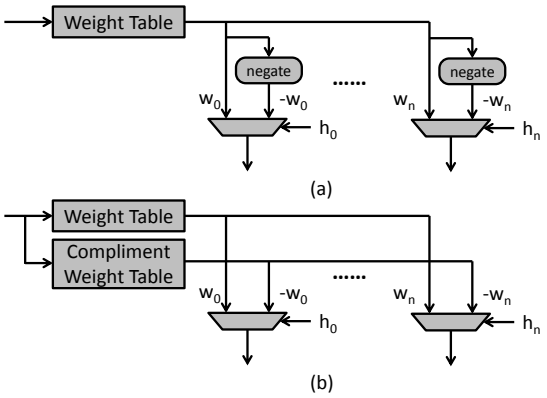

Fig. 5: Perceptron multiplication implementation.

IV. FPGA Implementation Optimizations

This section discusses FPGA-specific implementation optimizations for perceptron and TAGE. While this section assumes a modern Altera FPGA, the optimizations presented should be broadly applicable.

A. Perceptron Implementation

Section III-A introduced that perceptron predictor maintains vectors of weights in a table. It produces a prediction through the following steps: (1) a vector of weight (i.e., a perceptron) is loaded from the table. (2) multiply the weights with their corresponding global history (1 for taken and -1 for not-taken). (3) sum up all the products, predict taken if the sum is positive, and not-taken otherwise. Each of these steps poses difficulties to map to the FPGA platform. The rest of this section addresses these problems.

1) Perceptron Table Organization: Each weight in a perceptron is typically 8-bit wide, and perceptron predictors usually use at least 12-bit global history [5]. The depth of the table, on the other hand, tends to be relatively shallower (e.g. 64 entries for 1KB hardware budget). This requires a very wide but shallow memory, which does not map well to BRAMs on FPGAs. For example, the widest configuration that a M9K BRAM on Altera Stratix IV chips is 36-bit wide times 1k entries [4]. If we implement the 1KB perceptron as proposed by Jiménez et al. [5], which uses 96-bit wide perceptrons with 12-bit global history, it will result in a huge resource inefficiency as shown in Fig 4. Stratix IV chips have another larger but slower and fewer M144K BRAM on Stratix IV chips [4], which can be configured as wide as 72-bit times 2K entries, clearly the inefficiency problem persists and it would impact maximum operating frequency.

Since typically the perceptron table does not require large storage space, the proposed perceptron implementation uses MLABs as storage, which are fast fine-grain distributed memory resources. Since 50% of all LABs can be configured as MLAB on Altera Stratix IV devices, using MLABs does not introduce routing difficulty.

2) Multiplication: The multiplication step calculates the products of a weights in a perceptron and their global direction histories. Since the value of the global direction history can only be either 1 or -1, the "multiplication" degenerates to two cases, i.e., each product can either be the true form or the 2's compliment (i.e., negative) form of each weight. A straight forward implementation is to calculate the negative of each weight and use a mux to select between them based on the corresponding global history, as shown in Fig. 5(a). To improve maximum frequency, when updating perceptron in execution stage where the branch is resolved, both positive and negative forms of the updated weight can be calculated, and the negatives can be stored a complement perceptron table. In this way, the multiplication step requires only a 2-to-1 mux, as shown in Fig. 5(b). As a tradeoff, it requires extra storage for the negative weights.

3) Adder Tree:

B. TAGE Implementation

V. Evaluation

Range from 1KB-32KB Perceptron doesn't work well TAGE overriding with statistic corrector

VI. Conclusion

The conclusion goes here.

References

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