BRUMA: Generalizing All Preemption Functions

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Abstract—This paper presents BRUMA (Block Resizing for UnderManned Amount of Assays Avoidance), a method for generalizing all preemption functions currently used in preemptive RANSAC. BRUMA is inspired in the standard preemptive RANSAC preemption function and brings extra flexibility in the existing parameters while including new ones. By varying BRUMA parameters it is possible to deal with all currently available preemption schemes. This article also includes the results of some initial experiments that show that BRUMA achieved a performance similar to standard preemptive RANSAC, with cases where BRUMA has superior performance.

Keywords-preemption function; preemptive RANSAC; generalization; optimization; real-time SfM.

I. INTRODUCTION

The problem of accurately estimating good approximations for mathematical problems might lay on several kinds of approaches. In the last thirty years RANSAC (Random Sample Consensus) [1] has dealt with such estimation problem achieving notoriety mainly in fields like of Computer Vision (CV) and 3D Reconstruction (3DR).

RANSAC operations may be summarized as: Generate hypotheses from subsets of observations and evaluate the first against all the available observations in order to discover which hypothesis is the best approximated representative of the entire population. RANSAC keeps working until it reaches a confidence threshold.

Nevertheless, the standard algorithm has inadequate performance in some cases. This leads to the publication of several methods that target the goal of speeding up RANSAC tasks. Facing a trade-off between quality and time consumption researchers start to work in three major branches attempting to achieve better results: Propose an alternative hypothesize-and-verify method, improve hypotheses generation and improve hypotheses evaluation.

The first branch has a variety of works like MLESAC [2], AMLESAC [3], KALMANSAC [4], PROSAC [5], GASAC [6] and GOODSAC [7]. All of them execute hypothesize-and-verify tasks but each one has its own particularities, leading to algorithms that are efficient for specific classes of application.

The second branch consists of speeding up the hypotheses generation process or enhancing their quality in order to decrease the number of generation rounds. Nistér's Efficient Five-Point Algorithms [8][9] and hypotheses generation using Graphics Processor Units (GPUs) are examples of this approach.

The third branch focuses on accelerating evaluation process or, alternatively, detecting a condition that avoids unnecessary exhaustive verification. This anticipation in ending a task is often called preemption and it is the way we choose for improving hypothesize-and-verify performance (RANSAC in our work).

Among the available preemption schemes two deserve attention, namely the Randomized RANSAC [10] that executes anticipate evaluation and Preemptive RANSAC [11][12] that deals with restricted time and allows Real-Time (RT) performance (or near to RT).

Preemptive RANSAC employs a function in order to identify the moment of preemption. This concept is simply and powerful, but the function defined in Nistér's work is very dependent on number of hypotheses and observations to work properly.

We propose an improvement for eliminating such dependency. This work presents BRUMA (Block Resizing for UnderManned Amount of Assays Avoidance), a function that promotes a generalization of preemption functions and allows parameters variation to avoid some known limitations of Preemptive RANSAC [13].

This paper is organized as follows, Section II describes BRUMA, while Section III details the experiments carried out to validate our proposal and Section IV presents our conclusions.

II. BRUMA

BRUMA is a generalization of preemption functions that allows parameters variation as a way of adapting to diverse scenarios. Before presenting the equation behind BRUMA it is necessary to introduce a classification concerning several different ways a function may preempt. The following schemes are available.

Depth-first – the emphasis is on testing a single hypothesis against all observations; preemption occurs when the hypothesis accumulates a high amount of error (threshold) or if it achieves the desired confidence. Its scoring is mathematically expressed as:

$$\forall h_i, \pi_m(h_i) = \sum_{j=1}^{m} \rho(o_j, h_i), \qquad (1)$$

where π_m denotes the objective function, h_i is the i-th hypothesis under evaluation, o_j is the j-th observation considered on scoring, m is the number of available observations and ρ is the scoring function that returns a scalar value to compose the final hypothesis score.

Breadth-first – a purely breadth-first preemption scheme rejects hypotheses very early; it may affect the quality of winner hypothesis due to the risk of discarding good hypotheses that faced bad observations. The following expression describes scoring task.

$$\forall o_j, \pi_n(o_j) = \sum_{i=1}^{n} \rho(o_j, h_i) \qquad , \qquad (2)$$

where n denotes the amount of available hypotheses.

Hybrid – it is the combination of previous schemes and may emphasize depth or breadth evaluation. Preemptive RANSAC emphasizes breadth, since it allows more coherent hypotheses rejection. The hybrid scheme scoring works according to (3).

$$\forall o_j, \pi_n(o_j) = \sum_{i=1}^{n} \rho\left(o_j, h_{i|j}\right), \qquad (3)$$

where $h_{i|j}$ denotes that the chosen hypothesis depends on the observation, which are grouped in blocks.

After presenting different schemes for dealing with observations and hypotheses, it is possible to focus on preemption function. The function defined by Nistér in Preemptive RANSAC is given bellow:

$$f(i) = \left\lfloor M \cdot 2^{-\left\lfloor \frac{i}{B} \right\rfloor} \right\rfloor, \qquad (4)$$

where $\lfloor \cdot \rfloor$ denotes the floor operation, M is the amount of hypotheses and B denotes a fixed block size (the amount of tested observations in an evaluation round).

From (4) we see that every time i is a multiple of B the function selects half of hypotheses (the set of best-scored ones) and keeps scoring in the new evaluation rounds until only the winner hypothesis remains or the time budget is exhausted (whatever happens before).

This powerful function has two independent parameters, one fixed (B) and the other variable (M). This behavior may lead to situations like small amount of tested observations when they do not have the expected proportion of both.

BRUMA is inspired in Nistér's function, but avoiding the cited weaknesses. The idea behind BRUMA is that by varying the block size (B) we have extra flexibility to prevent mentioned problems. This is the first benefit, but since B is not fixed anymore; we can adjust this parameter to each evaluation round. This second advantage together with the introduction of a third parameter allows BRUMA to generalize preemption functions as shown in (5).

$$f(i) = \left\lfloor M_i \cdot p_i^{-\left\lfloor \frac{i}{B_i} \right\rfloor} \right\rfloor, \qquad (5)$$

where M_i denotes the amount of hypotheses at the i-th execution step, p_i is a scalar responsible for indicating how many hypotheses must be rejected on a preemption round, B_i denotes the block size at the i-th execution step and the floor operator can be replaced by the ceiling operator, if desired.

Through this function it is possible to represent, for example, the depth-first scheme setting B_i fixed and equals to the total of observations. The parameters can vary free and independently, allowing BRUMA to deal with any other preemption scheme.

While BRUMA leads to some advantages in the theoretical scenario, we need to validate them in practice. Thus, we carried out experiments to verify the output of our BRUMA implementation.

III. EXPERIMENTS

The experiments were planned in order to validate BRUMA using the following criteria:

- Flexibility – are the addition of parameters and the freedom of changing the values of all parameters a welcomed flexibility tool or just a more complex scenario to work with preemption functions?
- Correctness – have the parameters variations resulted in a lower accuracy?
- Coverage – in which circumstances BRUMA completely avoids the problems that usually happen with standard preemption functions?

Experimental environment employed SfM Test Case Genarator; VXL 1.12.0 and VW34 (with modifications). We used the SfM Test Case Generator to generate ground-truth and testing data for further evaluation.

However, the SfM Test Case Generator depends on VXL, and the use of VXL and VW34 in a single project leads to linking problems, because both libraries have their own VNL project with some conflicting definitions.

We solved such problem by changing some VW34 definitions. We chose to do this instead of re-implementing Preemptive RANSAC on VXL because

VW34 has, besides this algorithm, the implementation of five-point method. This is important since we want to compare our method with Nistér's work. Other important change in VW34 is the addition of a method capable of performing hypotheses evaluation employing BRUMA as the preemption function.

Validation was performed by executing simulations using synthetic data disturbed by a Probability Density Function (PDF) with the same hypotheses generation algorithm for the two tested preemption functions.

Simulations employed polygon format files (PLY files) with distinct numbers of vertices. Besides the models, we also varied noise level (standard deviations of 1, 4 and 16 pixels in the projection planes) and time budget (16.667 ms, 33.333 ms and 66.667 ms, i.e., processing rates of 60, 30 and 15 frames per second).

We were interested in metrics like the translational error, the number of performed assays and the total number of consumed observations. We measured translational error in degrees, computing the angle between the estimated translation vector and the ground-truth vector, while the number of assays and number of consumed observations are reported by our program.

An assay is employed here as an abstraction of steps executed to evaluate and score a hypothesis. They are, generally, the computation of the distance to the epipolar line, of residuals, the approximation to a PDF and so on. Any notion of steps that performs evaluation and scoring may be named as assay with the purpose of fairly comparing a set of preemption functions.

An important configuration in these experiments was the block size. Nistér proposed 100 as a reference size to use in applications due to the tolerable error magnitude, thus allowing a maximum of eight preemption rounds with fixed block size until only a single winner hypothesis remains (M is fixed and equals to 500).

While the simulations maintained this configuration when testing Nistér's preemption function, BRUMA was tested with varying block sizes. In these experiments we chose the following block size sequence for each round: 64, 70, 72, 80, 96, 192, 320, and all the remaining observations. The idea was that by starting preemption early we can evaluate a larger fraction of hypotheses and consume more observations. However, this may result in an increase in error magnitude.

We chose this block size sequence to speed up the execution of the first rounds, while giving more time to the later rounds, when most promising hypotheses survived. A more careful choice may result in more controlled gains (accuracy, performance).

Fig. 1 is a graph of relative performance. The ratios were computed dividing the mean of BRUMA performance by Nistér's method considering the total of remaining observations, the number of executed assays and the error magnitude as criteria in around 6,000 trials. Mathematically, it is as follows:

$$Ratio_{Metric} = \frac{Mean_{BRUMA}}{Mean_{Nistér}} . \qquad (6)$$

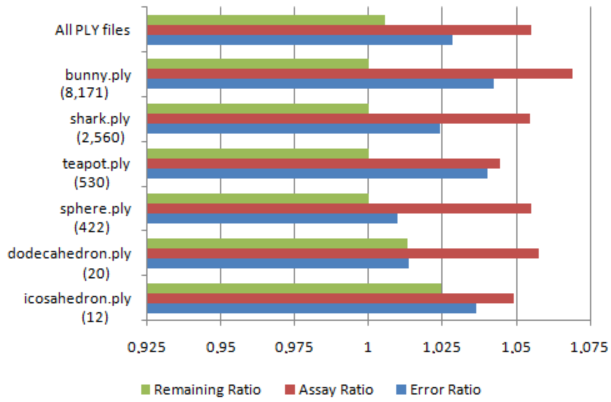

Figure 1. Relative ratios between preemption functions (BRUMA/Nistér's); numbers within brackets denote the number of vertices of each model

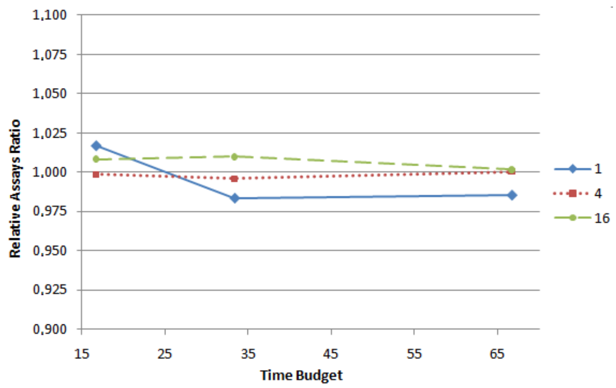

Figure 2. Assay ratio between preemption functions (BRUMA/Nistér's) correlating noise and time budget

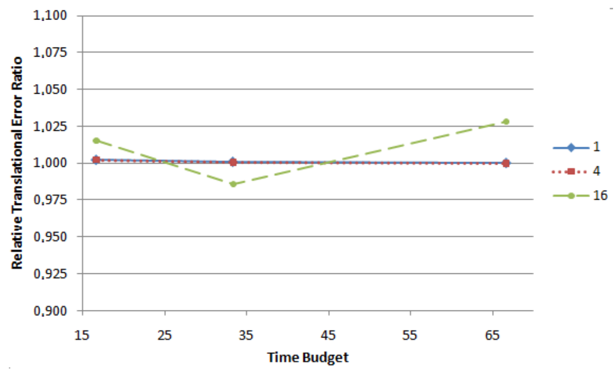

Figure 3. Error ratio between preemption functions (BRUMA/Nistér's) correlating noise and time budget

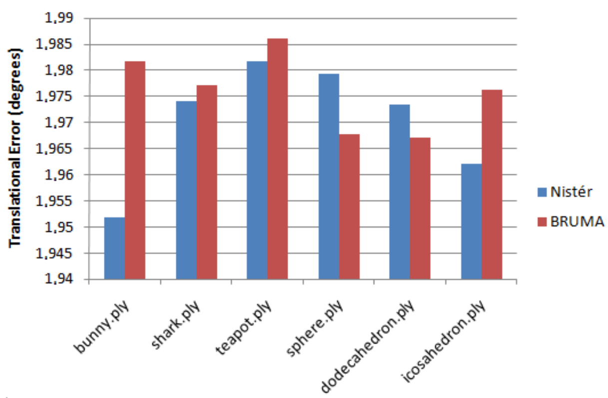

Figure 4. Mean of translational error grouped by model

At the first look, Fig. 1 displays Nistér's preemption function as the best choice once all the ratios are at least equals to one. But the correct interpretation depends on correlating ratios' information and on analyzing also Fig. 2, Fig. 3 and Fig. 4.

Observing the remaining ratio it is possible to see that except for the models with very few vertices (icosahedrons and dodecahedron) there is a well defined behavior: The ratio of distinct models is around 1 indicating no enhancing or reduction in coverage. It is against the expectations, but there is a good reason for this: Lack of time due to the small time budgets.

The values chosen for the time budget parameter were deliberately small to preserve good response time and attempt to work in real time with the side-effect of not allowing a complete coverage (of observations) depending on the model complexity.

By correlating the assay and remaining ratios we can notice the absence of a linear relation. Nevertheless, this correlation partially confirms the flexibility criterion by a simple reason: If the number of consumed observations remains stable and number of assays increase, it means that more distinct hypotheses have been tested against the same set of observations.

Finally, we achieved a lower accuracy (as expected) due to the early hypotheses elimination. Since the error and the assay ratios are not linearly proportional to the other ones we decided to analyze them in more detail, and neglect the remaining ratio (the most stable).

Fig. 2 reveals a correlation between time budget and noise level. Assay ratio has a tendency of decreasing as time budget increases considering the same noise level. BRUMA tested more distinct hypotheses than Nistér's approach for the highest noise level, thus, increasing the chance of finding a better solution; for the lowest noise level BRUMA was more efficient in this sense only for the smallest time budget, while for the middle noise level the results are very similar.

Fig. 3 demonstrates a slight error increase in the presence of small noise levels that decreases softly as the time budget increases. In the presence of a higher noise level, the error ratio changes abruptly; making BRUMA the best choice at the intermediary time budget and the worst when time restriction is relaxed.

Fig. 4 reports mean translational error in both preemption functions. Scale of error is highlighting the difference between preemption functions.

Nevertheless, both results are close; for instance, focusing on bunny.ply model the difference is around 0.03 degrees. Fig. 4 also confirms the feeling about results dependency on used model.

IV. CONCLUSION

This work presented BRUMA, a generalization of preemption functions as well as preliminary experiments comparing a single BRUMA block size sequence configuration and the setup suggested in Nistér's work.

The error ratios and the mean translational error showed that the results obtained by this first BRUMA configuration and Nistér's Preemptive RANSAC are very similar for the two lower noise levels used. We can also see that, for the highest noise level, BRUMA outperformed Nistér's Preemptive RANSAC for the 33.333 ms time budget, and performed worse for the other two time budgets.

Summarizing, the way BRUMA generalizes preemption functions does not merely increase the complexity of the application, but opens the possibility of new performance gains. From the preliminary results, it is possible to assert that some configurations may surpass standard preemptive RANSAC.

We are currently performing more simulations in order to find the best possible preemption function for the models we used in our experiments.

Besides that, we are also working on a scheme for selecting the block sizes for each round based on the number of vertices of the model, which may also incorporate information about the noise level, time budget and maximum expected error.

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