Learning-Based Branch-and-Bound for Template Matching

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Introduction

Branch-and-Bound (B&B) is a general technique for accelerating brute-force search in large domains. It is used when a global optimality is desirable, while more efficient optimization methods (like gradient descent) are irrelevant (e.g., due to the minimized function being nonconvex). A particular example of interest, very common in computer vision, is that of template matching (or image alignment), where one image (the template) is searched in another. This is useful, for example, in applications like stitching of panoramas, object localization and tracking.

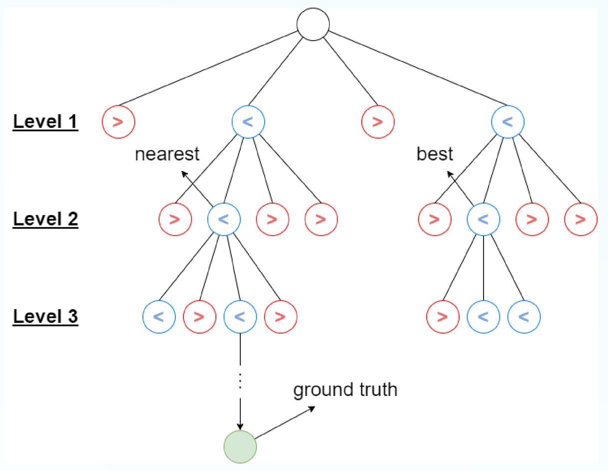
FAsT-Match (Fast Affine Template Matching) is an algorithm designed by Simon Korman, Daniel Reichman, Gilad Tsur and Shai Avidan (source) to search a fixed template inside an image, using the B&B technique.

The template which the algorithm is trying to find, can be found under an arbitrary affine transformation, therefore the number of transformations to consider is huge.

On each level of the algorithm, we check many transformations (also called configurations) which are spread along the search space. Each configuration is characterized by the photometric distance between the template and the place on the image where this configuration transforms the template into, on sampled points. At the end of each level, we are left with an array of such distances, and we need to decide around which configurations to expand. Therefore, we use a threshold (the higher bound) on those distances' values, computed as

$$threshold = minimum\ (called\ also\ best)\ distance + f(\delta)$$

The following figure demonstrates how B&B works in FAsT-Match:



The configurations in red were not close enough to expand in the next level ($distance > threshold$), while the configurations in blue, passed the threshold and therefore were chosen to be expanded in the next level of the algorithm ($distance < threshold$).

The $f(\delta)$ part of the bound is a linear combination of the parameter δ of the algorithm, which specifies the grid resolution of the search space, and is lowered by the same factor each level. This linear combination has been computed manually through trial and error and it uses only one parameter – δ (delta). Because of those reasons, it is not always optimal.

Definition

To tackle this issue, we reimplemented the FAsT-Match algorithm in Python and improved the decision process of the abovementioned higher bound by designing a Neural-Network model, resulting in time and accuracy improvement of the FAsT-Match algorithm.

In detail, we modified the threshold to be

$$threshold = minimum\ distance + f(set\ of\ features)$$

While the $f(set\ of\ features)$ part is now computed by the Neural-Network model, and it isn't only using a single parameter but a set of features (which includes delta).

The value which our model returns, ideally should be higher than the distance of the nearest configuration in the level, the one which on expansion will eventually get us to the real configuration of the template – the ground truth (green circle in the left figure).

Implementation & Samples Collection

First, we implemented the algorithm in the Python programming language, by translating the original code from its MATLAB version.

Afterwards, we created a data-base which we could use later for the Neural-Network training process. We collected 100 random images from the Internet and on each image, we ran the algorithm on 100 random templates inside the image. Each level of the algorithm provided us with the following data which we collected:

- The image dimensions
- The template dimensions
- The ratio between the average pixel value in the template to the average pixel value in the image
- The template smoothness (average template derivatives)
- The template pixels' standard deviation
- δ – grid resolution. The one value which the higher bound in the original implementation of the FAsT-Match algorithm is computed by
- Data about the distance array of the current level's subspace: minimum distance, average distance, distances standard deviation, percentiles (5, 10, 15, …, 95), distances range, distances amount (total number of configurations in the current sub-space).
- Affine matrix of the configuration with the minimum distance.

Total number of features collected: 37, as well as the ideal higher bound which we'll use as the target output of the model.

In addition, in a different file we stored for each level the minimum and maximum distance values and the histogram values of the distance array divided into 100 bars. This data was collected to estimate the model's accuracy – the percentage of the sub-space which is higher than the higher bound.

In order to ease the process of samples collection, we divided the images into 20 folders and ran the algorithm on them concurrently. We collected 73.5 KB of 68854 samples, with total computation time of 121.86 hours.

Deep-Learning Model

The next step was to implement a Machine-Learning/Deep-Learning model which upon integration in the algorithm, will choose the optimal bound and improve the algorithm run-time and accuracy.

At first, we were required to do some research in those areas and learn how to implement such a thing and what is the best model for our problem. Then, we chose to use Multi-Layer Perceptron for Regression model, which is a simple Neural-Network consisting of some fully-connected linear layers.

Additionally, we decided to use only 10 out of the 37 features which we collected on our samples, because after the collection process, we noticed that many features were highly correlated or not necessary for our model. The 10 features used:

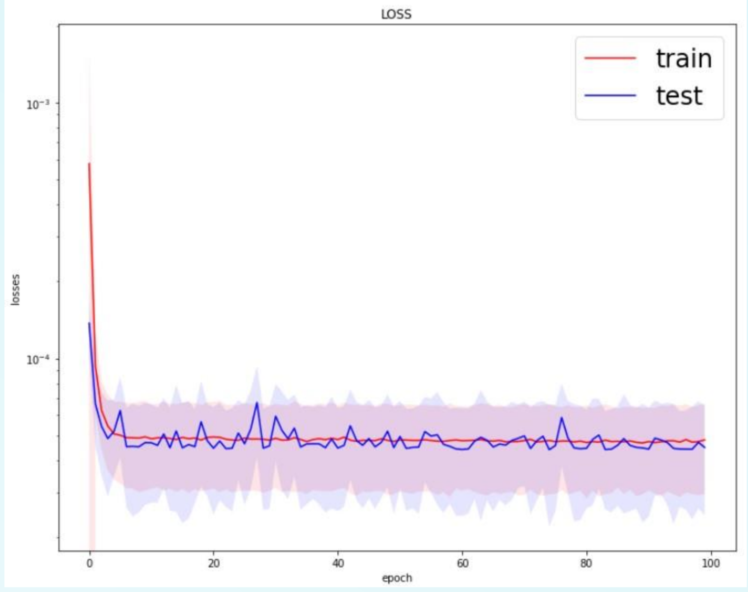
- The template dimensions
- The ratio between the average pixel value in the template to the average pixel value in the image
- The template smoothness (average template derivatives)
- The template pixels' standard deviation
- δ – grid resolution. The one value which the higher bound in the original implementation of the FAsT-Match algorithm is computed by
- Data about the distance array of the current level's subspace: minimum distance, average distance, distances standard deviation, distances range, distances amount (total number of configurations in the current sub-space).

Deep-Learning Model Cont.

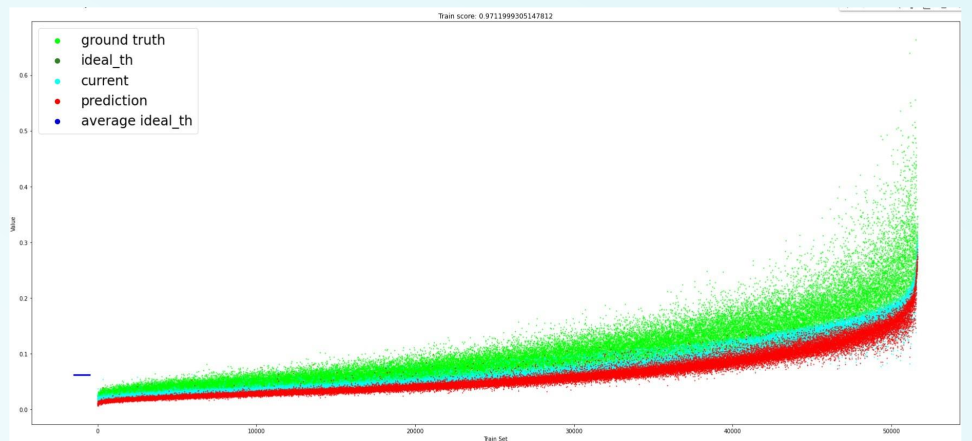
The process of choosing the model's parameters was conducted mainly by trial and error, and estimating the model performance by the following values:

- Loss – we used MSE (squared distance between the target and the model's prediction) as our model Loss-Function.
- Score – the ratio between our loss to the loss we would have got if we were predicting the average target value every time.
- Accuracy – percentage of times we succeeded on passing the ground-truth configuration to the next level in the algorithm ($prediction > ground\_truth$).

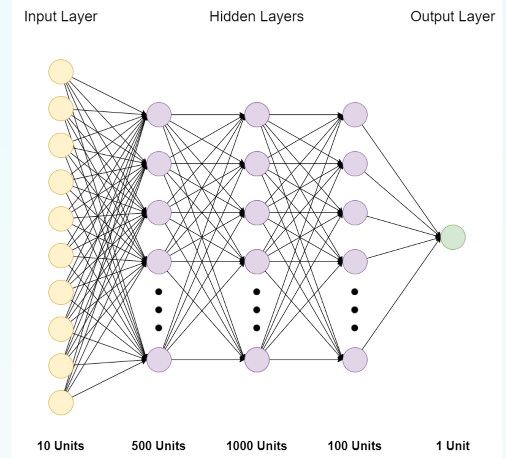
Example loss-per-epoch graph:



Model predictions on training-set graph:



After many trials, we came at our final model configuration:



With Tanh activation function and the following hyper-parameters:

$$number\_epoch = 100$$
$$size\_minibatch = 100$$
$$learning\_rate = 0.00001$$
$$weight\_decay = 0.000001, (for\ ADAM\ optimizer)$$

Testing & Results

The last step of the project was to check whether integrating this model in the FAsT-Match algorithm can improve its speed and accuracy results.

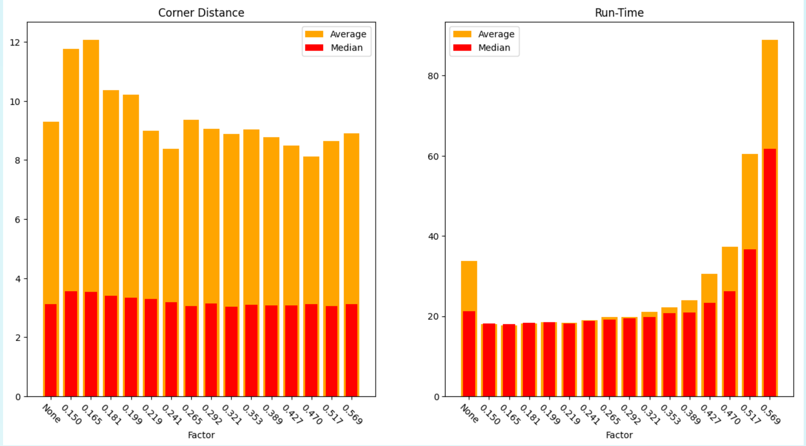
We ran on various target values to compare the results of each of them to the version of the algorithm without any such model.

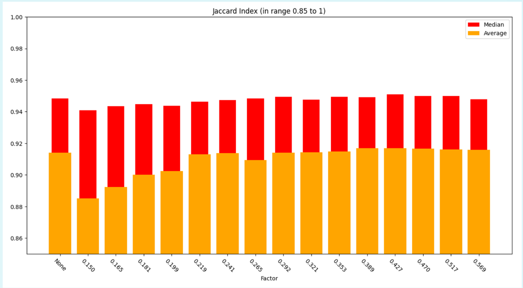
The target value that was used is:

$$\min\_distance + factor * (ground\_truth - \min\_distance)$$

Every time, we checked on a different set of factor values and continued to search around factor values which gave us good results. We compared the speed results by the average time per run, and the accuracy results by the Jaccard Index (union over bound) as well as the average distance between the corners of the found template to the ground truth one.

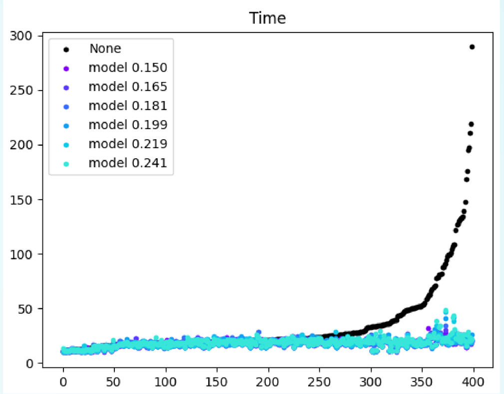
On the final round, we measured the results of 15 models with factor in the range 0.15-0.6 and got the following results on 400 test runs:





We can clearly notice the trade-off between accuracy and run-time. For instance, models with factor in range 1.5 to 2.1 got corner distance values higher and Jaccard index values lower than the rest of the models, while models with higher factor values got good accuracy results but it took them more seconds to complete a run.

We can also notice by comparing to the first bar which represents the previous method (without model), that our models can barely improve the accuracy, but they can improve the speed of the algorithm, mainly the worst cases as indicated by the average value of the bar in the Time graph. This worst-case improvement is demonstrated in the following graph which shows the time results on 400 runs (on each model), sorted by the time values got on the runs without any model (in black):



We could use this trade-off to integrate the desired model according to the purpose of our usage of the algorithm, but if we would have needed to choose one model which works good generally, we would integrate the model with the factor 0.241 for its good speed results and slight accuracy improvement.

This improvement shows that the use of such model in the FAsT-Match algorithm increases its stability in terms of speed, while keeping the same quality of results.