A Genetic Algorithm for HMI Test Infrastructure Fine Tuning

Lukas Rosenbauer[1], Anthony Stein[2] and Jörg Hähner[3]
[1]*BSH Hausgeräte GmbH, Im Gewerbepark B35, Regensburg, Germany*
[2]*Artificial Intelligence in Agricultural Engineering, University of Hohenheim, Garbenstr. 9, Stuttgart, Germany*
[3]*Organic Computing Group, University of Augsburg, Am Technologiezentrum 8, Augsburg, Germany*

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Abstract: *Human machine interfaces* (HMI) have become a part of our daily lives. They are an essential part of a variety of products ranging from computers over smart phones to home appliances. Customer's requirements for HMIs are rising and so does the complexity of the devices. Several years ago, many products had a rather simple HMI such as mere buttons. Nowadays lots of devices have screens that display complex text messages and a variety of objects such as icons. This leads to new challenges in testing, the goal of which it is to ensure quality and to find errors. We combine a genetic algorithm with computer vision techniques in order to solve two testing use cases located in the automated verification of displays. Our method has a low runtime and can be used on low budget equipment such as Raspberry Pi which reduces the operational cost in practice.

1 INTRODUCTION

HMIs enable customers to interact with a product. They can be rather simple components such as rotary knobs or sliders. Expensive devices can offer more complicated HMIs such as voice control, gesture control, or touch displays which offer even more ways to interact with a device.

These advances have led to new challenges in the development of the aforementioned solutions. An essential part of development is the verification of the product. The testing of HMIs has undergone serious investigation from various perspectives. Mateo Navarro et al. (2010) examine HMI testing from a software engineering point of view and propose an architecture for *graphical user interface* (GUI) testing. Duan et al. (2010) developed a model-based approach to achieve a high code coverage and to keep the development cost in bounds. Howe et al. (1997) exploit planning techniques in order to generate test cases for GUIs using evolutionary methods. A *genetic algorithm* was used by Rauf et al. (2011) to improve the path coverage of GUIs.

The aforementioned approaches deal with the question: *How* should HMI testing be done? With the move from manual testing to automated testing, another task is to provide the right tools for testers to implement tests. Inadequate test infrastructure is responsible for major economical losses (Hierons, 2005). Thus it is a profitable goal to provide testers with the right testing equipment.

Within this work, we combine an evolutionary algorithm with more traditional computer vision algorithms to solve two use cases for the visual validation of GUIs. Both deal with the identification of GUI elements. The first deals with the verification of screens from simulations or the framebuffer based on the designer's specification. The latter does not require the entire HMI as only the buffer and the CPU are necessary. The second one is a part of the electronic component test which has the goal to verify the software's behaviour combined with the hardware of the HMI. There we try to recognize various icons.

Both problems could be solved by using artificial neural networks. However, these have the downside that the number of possible classes must be known during the design time of the network (Géron, 2017). Usually testing is started early (Olan, 2003) and requirements change during the lifetime of a project (Nurmuliani et al., 2004) which might lead to frequent redesigns and retrainings of the specified neural network. Another downside is that usually an Nvidia GPU must be acquired in order to have reasonable runtimes (Géron, 2017).

We deemed this as unfavorable and thus took a look at more traditional computer vision methods such as *template matching* or *feature detectors* that do not have these downsides (Szeliski, 2010). On the

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other hand, they require the correct calibration of for example edge detection thresholds. In order to avoid calibrating these parameters manually, we apply a *genetic algorithm* (GA) to do this automatically.

Further, we provide a proof of concept that a GA can be used to automatically fine-tune computer vision methods for HMI testing. In our experiments we show that our calibrated recognition methods are not only able to correctly identify GUI elements, but that our calibration approach also needs a comparably small amount of data. Furthermore, our experiments reveal that the designed methods have a rather low runtime which enables us to test more screens and the designed approach can also be used on low-budget boards such as Raspberry Pi.

In Section 2 we discuss related work. We provide a more detailed description of the use cases in Section 3. Afterwards, several computer vision methods are introduced that we are going to calibrate (Section 4). This is followed by a description of our fitness function and GA (Section 5). In Section 6 we perform a series of experiments that verify our approach. We close the paper with a conclusion (Section 7).

2 RELATED WORK

HMI testing got into the focus of several companies. For example Froglogic's *Squish* framework or Bosch's *Graphics Test System* offer various functionalities for GUI verification. Some of these software products enable test engineers to use trained machine learning models such as neural networks for *optical character recognition* (Froglogic, 2020). Others require the manual calibration of algorithmic parts for the recognition of GUI elements, for example the test system of the company Zeenyx (2020). Some of these visual testing frameworks have found their way into various companies (Alégroth et al., 2016).

From a scientific point of view, the visual verification of GUI elements such as icons is an application of *computer vision* (CV). This problem is known as *object recognition* (Szeliski, 2010). This can be achieved by using artificial neural networks (Géron, 2017). There are also possible solutions outside of machine learning such as feature detectors (Lowe, 1999). It is worth mentioning that these CV methodologies also require a precise calibration of the underlying parameters in order to work properly. Further, the quality of the image recognition algorithms has been detected as key issue in visual testing and several enterprises encountered issues with the frameworks available (Alégroth et al., 2013).

GAs have been used for a variety of calibration tasks such as spectroscopy (Attia et al., 2017) and energy models (Lara et al., 2017). We think that these positive results indicate that a GA might also be useful to fine-tune CV methods for HMI verification. It is also worth mentioning that there a variety of alternative evolutionary techniques as documented in the survey of Stegherr et al. (2020). However, due to the aforementioned successful usages of GAs we decided to start with this class of metaheuristics.

3 PROBLEM DESCRIPTION

Within this section, we introduce our two use cases. We provide several example images to ease understanding and show how they can be solved using pure CV.

3.1 Verification on a Pixellevel

Before the images of an application are displayed, they are usually held in a framebuffer. When it is time to be shown on the display then the currently displayed image will be deleted. Afterwards, the next screen is loaded from the buffer to the display. During this process errors might occur as pixels are not properly loaded, old pixels are not deleted, or the image already contains errors in the buffer. We displayed such a case that we encountered in a company in Figure 1 where the word "Wecker" contains a pixel error (some pixels of characters are black but should be white).

In order to detect pixel errors, *template matching* (TM) can be applied Szeliski (2010). TM uses an example image called template and compares it to the image of an application. If both images are close enough in terms of a similarity measure or distance, then it is regarded as a match. TM can also be used to validate parts of the application's output. In our example we discovered the error by rendering an image containing the word "Wecker" and sampling the screen.

There are several ways to acquire an exemplary image that can be used as a template. One possibility is to use the designer's specification of individual screens, another one is to use a *test oracle* (Ammann and Offutt, 2016) which proposes the correct screen based on the current GUI state. Due to technical limitations there might still be some differences between the template and the application. These minor differences can be tolerated and the screen can be seen as valid. For example, the designers might define the user interface's colors in a format that uses one byte per color channel (888 format) and the HMI uses a 686 format (6 bits for red, 8 bits for green, 6 bits for

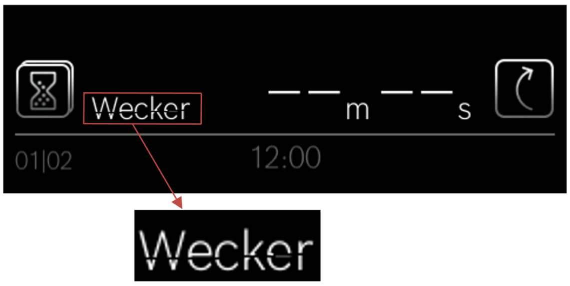


Figure 1: Example of a pixel error of an user interface. The word “Wecker” contains pixel errors as some of the white pixels are missing.

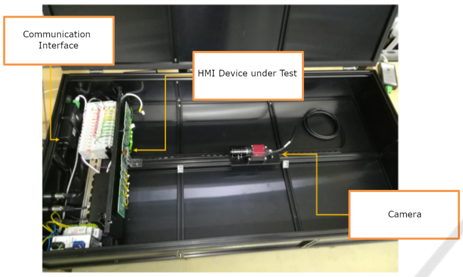


Figure 2: Example of a possible test environment for the component test of an HMI.

blue) to save memory. Such memory saving color formats are widespread in embedded systems (Marwedel, 2010) and a transformation from the 888 format to the 686 format is lossy.

TM requires test engineers to set tolerances or scale levels for the template. A too high tolerance leads to failures that go undetected in automated tests. An overly low tolerance can lead to false negative tests. The tolerances may differ from region to region. Thus the goal of this use case is to automatically set the correct thresholds for TM.

3.2 Component Test

Component testing is a branch of verification that limits its scope to a certain part of the system. An HMI can consist out of hardware and software. Both must interact properly in order to satisfy customers. For example, if a user selects a program on a dishwasher, corresponding options should be displayed.

A possible approach for a corresponding test environment is displayed in Figure 2. It consists out of a camera to make images of the display, the HMI which is to be tested, and a communication interface which can be used to manipulate its state. We packed these components in a black box in order to avoid side effects due to illumination. It is worth mentioning that we are not the first to evaluate a hardware using a camera. For example, Ramler and Ziebermayr (2017) used a camera-based testbed to verify the behaviour of a mechatronic system.

Images taken via camera contain a certain amount of noise due to the environment or the camera itself. Further, the HMI may not be parallel to the lens. This leads to slightly rotated GUI elements. A CV approach to tackle these problems are feature detectors such as *SIFT* (Lowe, 1999) which can be used to recognize rotated objects. Furthermore, a raw TM is also not sufficient since GUI elements will most likely not have the same scale as the template. In this use case we will fine-tune a CV method which combines feature detectors and TM.

4 COMPUTER VISION ALGORITHMS

Here we introduce two basic CV algorithms that are suitable for our two use cases, but they require the fine-tuning of certain parameters which we will do later on using a GA.

The first one is a simple template matcher described in Algorithm 1. It samples the given image using a sliding window with a step size of one pixel. If the patch is similar enough then it returns true. There can be several thresholds depending on the *region of interest* (ROI) of the screen. In our later experiments we will use the cosine similarity (Singhal, 2001).

Algorithm 1: Template matcher based on Szeliski (2010).

```
input : Image i, Template T
while Sample S left do
    if similarity(S, T) > Threshold then
        return True;
end
return False;
```

We further examine a feature-based approach which is based on *oriented fast and rotated brief* (ORB) (Rublee et al., 2011) and TM. We chose ORB over SIFT and SURF as it is a non-patented method which enables commercial use without licensing costs. Further, ORB is available in the well-known open source library OpenCV (OpenCV.org, 2020).

We once more sample the given image. ORB computes image features that are represented as bit vectors which can be compared to each other using the *Hamming similarity* (Rublee et al., 2011). For every patch we calculate the k best matches between the feature of the object to search for and the image to examine. Further, the average μ of these similarities is computed. Additionally we scale the template to various sizes, compare it with the patch, and return the highest cosine similarity γ. If the following condition holds we interpret that as a "found":

$$\beta \cdot \mu + (1-\beta) \cdot \gamma > \text{threshold} \tag{1}$$

where β is a real number between zero and one. It controls the influence of TM and ORB on the classification result.

We summarized this process for one sampled patch in Algorithm 2. Later on our GA will learn the number of scale levels, the scale increment, β, k, and the threshold. These can once more vary from ROI to ROI.

Algorithm 2: Object recognition with TM and ORB.

```
input : Patch p, Template T
t_feat = ORB_features(T)
p_feat = ORB_feature(p)
k_best = get_k_best_matches(p_feat, t_feat)
μ = mean(k_best_similarities)
tm_similarities = { }
for i in {-scale levels,...,scale levels} do
    // scale to 1 + i * scale_inc times its size
    scaled_temp = scale(T, 1 + i * scale_inc)
    // compute cosine similarity
    sim = cos_sim(p, scaled_temp)
    append sim to tm_similarities
end
γ = max(tm_similarities)
if β · μ + (1 − β) · γ > Threshold then
    return True;
return False;
```

5 EVOLUTIONARY FINE TUNING

Evolutionary heuristics such as genetic algorithms can be used to solve a variety of optimization approaches and were originally introduced by Holland (1992). Here we use a GA for fine-tuning existing CV methods. Thus we differ from GP approaches as these intend to optimize the structure of a CV process. Within this section, we introduce a fitness function and a GA for our use cases.

5.1 Fitness Function

The design of our fitness function has been inspired by the benchmarking of information retrieval systems such as search engines. The capability of a search engine to answer a query can be evaluated using a set of documents. Only a part of the documents are relevant for the query. The search engine returns a subset of the documents that it regards as important. The search engine's answer is then benchmarked by the number of relevant and irrelevant documents that it returned (Baeza-Yates and Ribeiro-Neto, 1999).

If an object recognition algorithm examines a set of images then it should only detect GUI elements that are available or in other words: There should be no false positives. This can be examined using the *precision* $P(\cdot,\cdot)$ of an object recognition algorithm A for a set of images S:

$$P(A,S) = 1 - \frac{|\mathrm{out}(A,S) \setminus \mathrm{ob}(S)|}{|\mathrm{out}(A,S)|} \tag{2}$$

where $\mathrm{ob}(S)$ represents a list containing the objects on the set of images and $\mathrm{out}(A,S)$ represents a list containing the objects that the algorithm claims to be on the images. The elements of both lists are tuples of the form (i, ob) where i is an image of S and ob is an object. P ranges from zero to one. The best possible value of one indicates that an algorithm only detected objects that were actually on the given images. A value lower than one indicates that the algorithm detected objects that are not there. In our analogy the precision measures the amount of relevant documents among the retrieved ones.

Further, a recognition method should not miss any object. This can be measured via the *recall* $R(\cdot,\cdot)$:

$$R(A,S) = \frac{|\mathrm{ob}(S) \cap \mathrm{out}(A,S)|}{|\mathrm{ob}(S)|} \tag{3}$$

Its values also range from zero to one. A value of one means that the method found all available objects. A smaller value indicates that the algorithm missed something. In information retrieval it is used to quantify the amount of relevant documents found by the method.

We combine both quality measures into one fitness function $F(\cdot,\cdot)$:

$$F(A,S) = \frac{P(A,S) + R(A,S)}{2} \tag{4}$$

We divide both values by two in order to norm the fitness values. Thus it also ranges from zero to one. A perfect algorithm that never misses an object nor detects objects that are not there is going to achieve a value of one.

5.2 Genetic Algorithm

Genetic algorithms are population based metaheuristics. Each element of the population represents a solution for the underlying optimization problem. During an iteration of a GA, two individuals are drawn from the population which is coined *selection*. These solutions are then combined to create two new solutions. This step is called *crossover*. Further, these two solutions may be changed randomly which is named *mutation*. After these operations the new solutions will be inserted into the population. The population has a fixed boundary. Whenever its capacity is reached, a deletion mechanism is used to make space for new solutions. This process is repeated until a stopping criterion is reached. Within this work we stop when a fitness level of one is reached. A corresponding pseudocode is displayed in Algorithm 3.

For our GA we use a binary tournament selection. Thus we draw two random solutions from the population and choose the one with higher fitness. This is repeated twice in order to get two solutions **x** and **y** that will be used for the crossover operation. For the latter we use an arithmetic crossover to generate two new solutions $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{y}}$:

$$\tilde{\mathbf{x}} = \alpha \cdot \mathbf{x} + (1-\alpha) \cdot \mathbf{y}$$
$$\tilde{\mathbf{y}} = \alpha \cdot \mathbf{y} + (1-\alpha) \cdot \mathbf{x}$$

where α is a number between zero and one.

The parameter k for the ORB algorithm is discrete. If our GA proposes a floating point number x for it then we will use $\lfloor x \rfloor$.

We apply a creep mutation. Each element gets a new value with a probability of p. Further, an elitist deletion mechanism is used and thus the elements with the worst fitness are deleted.

Algorithm 3: Pseudocode of the GA.

```
P = initialize_population()
while stopping criterion is not satisfied do
    Choose x, y from P via selection
    Create x̃, ỹ from x, y via crossover
    Mutate x̃, ỹ using p
    insert x̃, ỹ to P
    if population capacity exceeds limit then
        perform deletion
end
return best solution of P
```

The encoding of a solution is within this work specific to the computer vision algorithm that we evaluate. If we consider the template matching approach (Algorithm 1) then we have to determine three parameters per ROI (similarity threshold, number of scale levels, scale level increment). Our method that combines ORB with template matching (Algorithm 2) requires five parameters per ROI (similarity threshold, number of scale levels, scale level increment, k, β).

Table 1: Intervals of possible values for population initialization and mutation.

parameter	range
Algorithm 1 thresholds	$[0,1]$
Algorithm 2 thresholds	$[0,1]$
β	$[0,1]$
k	$[1,40]$
Scale levels	$[0,10]$
Scale increments	$[0,0.2]$

6 EVALUATION

For our evaluation we consider three industrial data sets of BSH Home Appliances. The company is a German producer of home appliances and develops various products ranging from ovens over dishwashers to fridges. For our pixel verification use case we acquired data of an oven project and for the component test use case we acquired data of a fridge and a dishwasher HMI.

The fridge data set contains 93 different icons to recognize which are distributed over two regions. We collected 8 sample images per icon and 8 additional images containing no icon at all. The dishwasher data set contains 23 different icons on 4 regions. We collected 10 images per dishwasher icon and an additional 10 images displaying no icon at all. For the oven data set we verify entire screens and collected 440 images. We use an 80-20 split to separate each data set into a training and a test data set.

We draw the new values during mutation or population initialization uniformly at random from Table 1. We use these intervals for all ROIs. We run each experiment a hundred times and run the GA until a fitness value of one is reached.

We additionally performed a preliminary parameter study for the GA. There the population sizes $100, 200, 300..., 500$ were studied. For α we considered $0.1, 0.2, 0.3, ...0.5$. Additionally we examined $0.02, 0.04, 0.6...0.12$ as values for p. Hence 150 different combinations have been evaluated for their convergence speed. We concluded that a suitable choice for α is 0.4, for the population boundary it is 200, and for p it is 0.1. It is worth mentioning that for all hyperparameter combinations we could achieve a fitness of 1.

For our experiments we used a Dell OptiPlex XE3 with 32GB RAM and an Intel i7 8700 processor and it was not used for anything else during the evaluation.

Table 2: Average iterations $\pm\sigma$ until a fitness value of 1 is reached (rounded to full iterations).

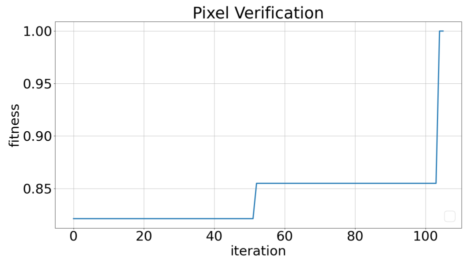
data set	region	iterations
Pixel verification	-	86 ± 11
Fridge	0	167 ± 17
Fridge	1	912 ± 83
Dishwasher	0	101 ± 7
Dishwasher	1	38 ± 3
Dishwasher	2	3 ± 1
Dishwasher	3	293 ± 21

6.1 Learning Process

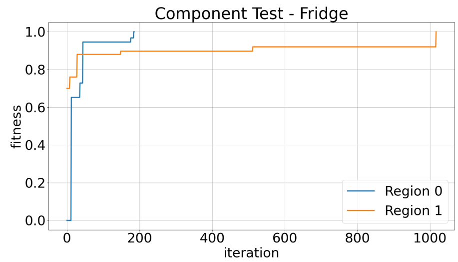
In Figure 3 we display the learning process of our GA on the three data sets. We decided to visualize the longest encountered runs as thus we show the experienced worst case behaviour and additionally give insight about the encountered fitness function. However, we also documented the average number of iterations until a fitness value of 1 is reached in Table 2. We could achieve fitness values of 1 on each test data set.

Figure 3 (a) shows the results for our oven data set (pixel verification). There we could achieve an optimal fitness value rather quickly and we could only observe three plateaus for the fitness function. The fitness function on the fridge data (Figure 3 (b)) is more diverse and the GA needs much longer to achieve an optimal value. Region 1 is harder to learn for the GA as it contains more icons. We could also observe differing learning times for the dishwasher data (Figure 3 (c)). Especially regions 2 and 3 are highly different. A closer look at our data revealed that region 2 is quickly learned because it only contains two rather distinctive icons. On the other hand, Region 3 displays connectivity icons. These are rather similar which leads to a need for a more precise set of parameters.

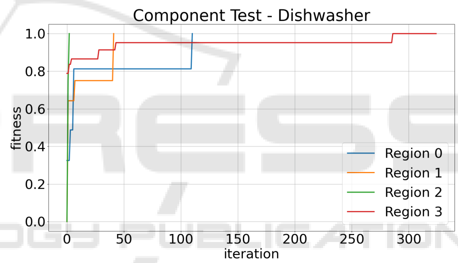
The averaged results displayed in Table 2 show that there is a certain amount of variance in the learning process of most regions. Furthermore, the average number of iterations until convergence is reached seems to differ from region to region. This can be verified using statistical tests. We employed a Friedman test whose null hypothesis is that the average number of iterations until a fitness value of 1 is reached is the same for all regions. We computed a p-value below 0.05 which we regard as significant. Thus we reject the null hypothesis and verify our observation that the region has an impact on the duration of the learning process.



(a) Longest encountered learning process for the oven data set.



(b) Longest encountered learning process for the fridge data set.



(c) Longest encountered learning process for the dishwasher data set.

Figure 3: Longest runs of the GA that we encountered during all performed experiment repetitions.

6.2 Dealing with Incomplete Data

Due to changes in requirements (Nurmuliani et al., 2004) and the practice of early testing (Olan, 2003), we think it cannot be assumed that all icons are known or implemented when testing starts. Hence we simulate that we lack the complete knowledge of all known icons. We drop a certain number of icons from the training set but keep them in the test set and evaluate if our calibrated CV methods are still capable of detecting the test data set correctly.

For these experiments we confine to the fridge data set as it contained the most icons and it was the data set where we measured the longest learning process. We concentrate on region 1. We drop 1,...,12 icons and observe the fitness values on the test data set. We repeat this 100 times for each number of icons to drop.

Table 4: Averaged runtimes in seconds separated by use case and region.

data	average runtime	σ	ROI size
pixel verification	0.0180	0.0080	943×186
Fridge	0.0284	0.0019	294×69
Fridge	0.0234	0.0019	273×65
Dishwasher	0.2186	0.0021	250×641
Dishwasher	0.0309	0.0018	204×111
Dishwasher	0.0299	0.0026	190×117
Dishwasher	0.0117	0.0011	98×83

Table 3: Averaged fitness values on the test data set of the fridge HMI if certain icons are dropped. For the first 8 icons no drop could be detected.

dropped icons	average fitness	σ
9	0.9827	0.00459
10	0.9783	0.00603
11	0.97810	0.00605
12	0.97482	0.00916

We summarized our results in Table 3. It can be seen that we can drop up to 8 icons without reducing the fitness on the test data set. If more icons are dropped we see a reduction in terms of the fitness. Hence, a calibration can deal with new icons that were not available during the training to a certain degree. If we had used a neural network then we would have had to adapt the network architecture (the output layer) and we would have had to retrain it in order to recognize the upcoming GUI elements. With our approach we need, in the worst case, a retraining but no adaptation of the model. Note that we could observe similar effects for the other two data sets.

6.3 Runtime Considerations

Testing pursues the goal to find errors and ensure product quality. However, the long-term goal of every company is to earn money. Therefore testing infrastructure should also be viewed from an economical point of view.

Table 5: Averaged runtimes in seconds for the Raspberry Pi setting.

average runtime	σ	ROI size
0.2618	0.0017	92×51
0.2065	0.0015	80×47
0.2158	0.0019	36×40
0.2656	0.0017	80×50
0.1980	0.0012	70×38

The runtime of a piece of testing infrastructure is crucial since it is a limiting factor for the number of tests that can be executed. High runtimes may lead to more test stands that must be acquired and maintained which in turn leads to a rise in development cost. Thus we shortly want to summarize and discuss the observed execution times on our desktop computer.

We measured the runtimes of the pixel verification method using images with a resolution of 943×186 pixels. We did the same for Algorithm 2 on the fridge and dishwasher images which have a resolution of 1490×423 and 1399×400 respectively.

The averaged results can be seen in Table 4. We used the combined training and test data sets for the estimation. Both algorithms have runtimes of less than one second and, if the regions are rather small, the execution time may be even less than 100 ms.

7 CONCLUSION AND FUTURE WORK

We examined two use cases located in the visual verification of *human machine interfaces* (HMI). There are already commercial solutions available which require test engineers to choose parameters of computer vision methods such as pixel verification manually. We developed a fitness function and employed a *genetic algorithm* to automatically fine tune existing computer vision models. Thus we could erase the tester engineer's pain of choosing parameters manually.

We performed a first proof of concept on several different industrial data sets. After a reasonable amount of training we were able to correctly identify icons and could detect pixel errors. Further, our designed algorithms have rather low execution times which enables us to run high numbers of tests.

Furthermore, we verified our approach on different hardware solutions (regarding computer and camera) where we were able to underline the hardware-independence of our method. This included Raspberry Pi setup which enables companies to cheaply apply our evolutionary technique (if compared to desktop solutions).

From an engineering perspective we are going to roll out our system in BSH Home Appliances. Our next scientific goal is to employ evolutionary techniques to other computer vision models.

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