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An autofocus heuristic for digital cameras based on supervised machine learning

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Abstract Digital cameras are equipped with passive autofocus mechanisms where a lens is focused using only the camera's optical system and an algorithm for controlling the lens. The speed and accuracy of the autofocus algorithm are crucial to user satisfaction. In this paper, we address the problems of identify when an image is in best focus and when individual objects within the image are in best focus. We show that supervised machine learning techniques can be used to construct a passive autofocus heuristic for these problems that out-performs an existing state-of-the-art hand-crafted heuristic. In our approach, training and test data were produced using an offline simulation on a suite of 25 benchmarks and correctly labeled in a semi-automated manner. A decision tree learning algorithm was then used to induce an autofocus heuristic from the data. The automatically constructed machine-learning-based (ml-based) heuristic was compared against the best previously proposed hand-crafted heuristic for autofocusing. In our experiments, the ml-based heuristic had improved speed—reducing the number of steps needed to focus by 63.6% in the best case and by 39.7% on average—as well as improved accuracy.

Keywords Autofocus · Live preview · Digital camera · Machine learning

1 Introduction

Modern digital cameras are equipped with one or more passive autofocus mechanisms. In passive autofocus mechanisms, a lens is focused using only the camera's

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optical system and an algorithm for controlling the lens. Passive autofocus mechanisms come in two basic kinds: contrast-detection and phase-detection. Contrast-detection autofocus is the most common—being standard in a wide range of cameras from mobile phones cameras, to point-and-shoots, to high-end DSLRs—whereas currently only high-end DSLRs also come equipped with phase-detection autofocus. Phase-detection is faster and better able to track subject movement, whereas contrast-detection is less costly and can be more accurate (Cicala, 2012). Our concern here is with contrast-detection autofocus.

In this paper, we address the problems of identify when an image is in best focus and when individual objects within the image are in best focus. The latter problem is important in focus stacking (see, for example, (Vaquero et al, 2011)), where a set of images is acquired and then merged in post processing in order to achieve a final image that is all-in-focus. We show that machine learning can be used to semi-automate the construction of heuristics for these problems. Our approach uses supervised learning. In supervised learning, one learns from training examples that are labeled with the correct answers. More precisely, each training example consists of a vector of feature values and the correct classification or correct answer for that example. In our approach, training and test data were produced using an offline simulation on a suite of 25 benchmarks, and correctly labeled in a semi-automated manner. Once the data was gathered, a decision tree learning algorithm (Quinlan, 1993) was used to induce a heuristic from the data. In a decision tree the internal nodes of the tree are labeled with features, the edges to the children of a node are labeled with the possible values of the feature, and the leaves of the tree are labeled with a classification. To classify a new example, one starts at the root and repeatedly tests the feature at a node and follows the appropriate branch until a leaf is reached. The label of the leaf is the predicted classification of the new example.

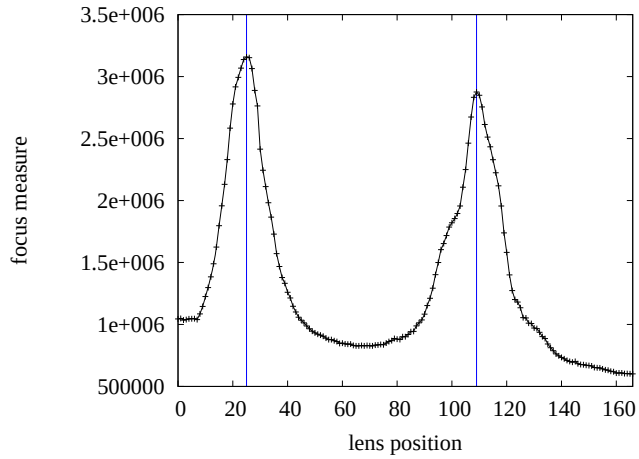
Once learned, the decision tree heuristic was compared against the best previously proposed, hand-crafted heuristic by incorporating the heuristics into a sweep focusing algorithm and applying the algorithm on a benchmark suite of images. On these benchmark suites, the automatically constructed decision tree heuristic had improved speed—reducing the number of steps needed to focus by 63.6% in the best case and by 39.7% on average—as well as improved accuracy.

2 Background

In this section, we review the necessary background in contrast-detection autofocus, focus measures, and focus search algorithms.

2.1 Focus measures

Contrast-detection autofocus makes use of a focus measure that maps an image to a value that represents the degree of focus of the image. Many focus measures have been proposed and evaluated in the literature (see, e.g., (Groen et al, 1985; Subbarao and Tyan, 1998)). In our work, we make use of an effective focus measure called the



(a)

(b) (c)

Fig. 1 (a) Focus measures of images at each of the 167 lens positions (Canon 50 mm lens) for an example scene using the squared gradient focus measure. The two (blue) vertical bars refer to the two images that have objects that are in best focus: (b) flower in focus, and (c) fern and grasses in focus.

squared gradient (Santos et al, 1997). Let $f(x,y)$ be the luminance or grayscale at pixel (x,y) in an image of size $M \times N$ pixels. The value $\phi(p)$ of the squared gradient focus measure for an image acquired when the lens is at position p is then given by,

$$\phi(p) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-2} (f(x,y+1) - f(x,y))^2.$$

Following Kehtarnavaz and Oh (2003), in our work we assume that the region of interest (ROI) is the entire image. In practice, a user can either (i) specify the ROI by moving a rectangle over the desired part of the image when the camera is in live preview mode, or (ii) have the camera automatically determine the object or region of interest to bring into focus (e.g., using face or object recognition (Lee et al, 2008; Rahman and Kehtarnavaz, 2008)). Our proposals are easily adapted to the case where the ROI is an arbitrary sub-area of an image.

2.2 Search algorithms

A contrast-detection autofocus algorithm iteratively moves the lens searching for a lens position that brings the image into best focus according to the focus measure. Lenses are moved by step motors that can be positioned at discrete positions. The images are acquired from the same stream of images that is displayed in the camera's live preview mode. (In live preview mode, the camera displays images streamed from the sensor at video frame rates; e.g., 24 frames per second on many Canon cameras.) Figure 1 shows the focus measures of the images acquired at all of the possible lens positions (Canon 50 mm lens) for an example scene.

Given a set of lens positions $\{a, a+1, \ldots, b\}$ from near focus to far focus, three autofocus search problems can be defined. The first search problem is to find the lens position that corresponds to the image with the *nearest* peak in the focus measure, where nearest can be either defined relative to the camera (i.e., nearest to a) or to the current position of the lens. The second search problem is to find the lens position that corresponds to the image with the *maximum* or *highest* peak in the focus measure. A third search problem, related to finding the highest peak, is to find *all* lens positions that correspond to a peak in the focus measure. In general, autofocus based on nearest peak may be preferred over that based on highest peak, as finding the nearest peak can be less costly than finding the highest peak and foreground elements are the subject in many common photography settings. However, a deficiency of autofocus based on nearest peak is that it can settle on bringing inconsequential objects into focus, whereas that based on highest peak can be more likely to bring the dominant object into focus or to bring most of the region of interest into focus. As well, finding the highest peak can be useful in situations where the focus measure is noisy and thus has false peaks (for example, in low light situations). Finally, the problem of finding all peaks is important in focus stacking (Vaquero et al, 2011), where a set of images is acquired and then merged in post processing in order to achieve a final image that is all-in-focus.

In this paper, we present a heuristic algorithm that identifies all lens positions $p \in \{a, a+1, \ldots, b\}$ such that the focus measure $\phi(p)$ is a peak and also finds the highest peak. At each iteration, step motors can be moved a single step or larger steps. For example, in the Canon DSLR cameras, the largest step size corresponds to eight single steps. Each step, small or large, is followed by a latency that can be hundreds of milliseconds. As well, step motors can suffer from backlash where the lens (or the software controlling the lens) loses track of the lens position when changing the direction of the lens movement (Kehtarnavaz and Oh, 2003; Morgan-Mar and Arnison, 2013). Thus, two desirable features of a search algorithm are that it (i) takes as large of steps as possible and (ii) minimizes changes in direction. The goal is to focus as quickly as possible without sacrificing accuracy.

Determining the maximum of a function over an interval that can be evaluated at discrete points can be solved using two generic search algorithms that are often used as points of comparison: Global search and Fibonacci search (we review autofocus-specific search algorithms in the next section). The *Global* search algorithm simply steps through all possible lens positions. Although impractically slow, the algorithm is guaranteed to find all peaks and to find the maximum value of the focus measure.

The *Fibonacci* search algorithm (Kiefer, 1953), in a manner similar to binary search, narrows at each iteration the interval in which the peak can lie. Fibonacci search is guaranteed to find the maximum in the *fewest* number of steps if the function is unimodal; i.e., has a single peak over the interval. Unfortunately, the assumption of unimodality usually does not always hold in our setting and even when it does hold, the back-and-forth movement of the algorithm is undesirable because of backlash.

3 Related Work

The problem of designing search algorithms for passive contrast-based autofocusing has been quite well-studied in the literature. However, the vast majority of the work has been on finding the nearest peak and there has been little work on finding the highest peak or on identifying all peaks.

3.1 Finding nearest peak

He, Zhou, and Hong (2003) propose a coarse-to-fine search, where initially the search algorithm takes coarse or large steps until a *nearest* peak is found and then reverses direction and takes fine steps to determine the peak. The idea of a coarse-to-fine search has been influential in subsequent work, including the present work.

Li (2005) proposes an algorithm that trades off accuracy for speed by only using a medium-sized search step to find the *nearest* peak. The algorithm is suited for mobile phone and compact cameras with a fast aperture (low f-number), where there is a large depth-of-field and the lens is relatively easy to focus as there are several indistinguishable (to the human eye) focus positions.

Chen, Hong, and Chuang (2006) propose an algorithm that iteratively samples the focus measures at various lens positions, fits an equation to predict the location of the *nearest* peak, takes coarse steps to be near the predicted peak, and finally takes fine steps within a bisection search algorithm to find the peak.

Supervised machine learning approaches to finding the *nearest* peak have also been proposed. Chen, Hwang, and Chen (2010) propose an algorithm that uses a self-organizing neural network to predict the location of the nearest peak based on sampling the focus measure at three places. Their approach is one of the first to be based on supervised machine learning techniques. Han, Kim, Lee, and Ko (2011) also use a supervised machine learning technique, a variation of 1-nearest neighbor, to predict the location of the nearest peak based on sampling the focus measure at three places. While these approaches are specific to the problem of finding the nearest peak, we adapt some of their features in our supervised learning approach to the problems of finding the highest peak and all peaks.

3.2 Finding highest peak and all peaks

Kehtarnavaz and Oh (2003) develop a rule-based autofocus algorithm to find the *highest* peak and *all* peaks over an interval by performing a full sweep (see Algorithm 1).

Algorithm 1: Kehtarnavaz and Oh (2003) rule-based search algorithm for finding a maximum of a focus measure $\phi(p)$ over a set of focus positions $p \in \{a, a+1, \ldots, b\}$.

```
   input : Function φ(p) and interval [a,b]
   output: Return maximum of φ(p) over p ∈ {a,a+1,...,b}
   k ← 0; down ← 0;
   F_Current ← 0; F_Max ← 0;
   p ← a;
   while p ≤ b do
       F_Previous ← F_Current;
       F_Current ← φ(p);
1      if k ≤ 5 then
2          stepSize ← Initial;
3      else
4          if F_Current ≤ 0.25 · F_Max then
5              stepSize ← Coarse; down ← 0;
6          else
7              D_F ← F_Current − F_Previous;
8              if D_F > 0.25 · F_Previous then
9                  stepSize ← Fine; down ← 0;
10             else if stepSize = Fine and D_F > 0 then
11                 down ← 0;
12             else if D_F < 0 then
13                 if stepSize = Fine then down ← down + 1;
14                 if down = 3 then stepSize ← Mid; down ← 0;
15             else
16                 stepSize ← Mid; down ← 0;
       if F_Current > F_Max then F_Max ← F_Current;
       k ← k + 1;
       p ← p + stepSize;
```

The hand-crafted rules predict whether to move the lens a coarse, medium, or fine step at each iteration as it sweeps the lens from near focus to far focus (Lines 1–16 in Algorithm 1). The goal of the heuristic is to move the lens larger steps but without missing any peaks in the focus measure. In our approach we use machine learning to devise a heuristic to determine the step size to move the lens. To the best of our knowledge, the rule-based algorithm remains the state-of-the-art and we perform a detailed experimental comparison of the rule-based algorithm to our machine-learning-based algorithm in Section 5. As well, as noted in Section 2.2, the Global search algorithm can be used to find all peaks and the Fibonacci search algorithm can be used to find the highest peak—provided the function is unimodal over the lens positions—and we also compare against these algorithms in Section 5.

4 Learning to Focus

In this section, we describe the methodology we followed to automatically construct a search heuristic for autofocusing by applying techniques from supervised machine learning. We explain the construction of the initial set of features (Section 4.1), the

collection of the data (Section 4.2), the use of the data to filter and rank the features to find the most important features (Section 4.3), and the use of the data and the important features to learn a simple heuristic for use within an iterative focusing algorithm (Section 4.4).

4.1 Feature construction

A critical factor in the success of a supervised learning approach is whether the features recorded in each example are adequate to distinguish all of the different cases. We began with sixty features that were felt to be promising. The features are all functions of the current value of the focus measure and previous values of the focus measure. The sixty features were a mixture of generalizations of previously proposed features and novel features. For previously proposed features, we generalized some of the features used in Kehtarnavaz and Oh's (2003) hand-crafted heuristic for choosing the next step size and He, Zhou, and Hong's (2003) ratio feature for deciding when to reverse the search direction.

We also created many novel features for autofocusing. A more accurate classifier can often be achieved by synthesizing new features from existing basic features, where here the basic features are the raw values of the focus measures. We constructed novel features by applying simple functions or combinations of simple functions to basic features. Examples of simple functions include comparison of two features, the ratio of two features, and the log of the difference of two features. Table 1 shows the full set of features that we considered. All of the features are Boolean valued except for the feature *downhillCount*, which is four-valued.

4.2 Data collection

In addition to the choice of distinguishing features (see Section 4.1 above), a second critical factor in the success of a supervised learning approach is whether the data is representative of what will be seen in practice. The experimental methodology for gathering representative data consisted of three stages. All implementations were in C++ running under Windows 7[1].

In the first stage, we implemented a camera remote control application whereby a camera is tethered to a computer via a USB cable and controlled by the software running on the computer. Our remote control application makes use of the Canon SDK (Version 2.11) and can control and replicate the basic functionality of the camera such as setting the aperture, displaying the live preview stream, and controlling the focus position of the lens. Using the remote control software, we gathered 25 sets of benchmark images that covered a range of common photography settings including landscapes, closeups, interiors, still lifes, and so on. Each of the sets of benchmark images contains either 167 (when using a 50 mm lens) or 231 (when using a 200 mm lens) jpeg images, one for each focus position of the lens. The jpeg images are

[1] The software and data are available at: `https://cs.uwaterloo.ca/~vanbeek/research`.

Table 1 The full set of sixty features considered in the machine learning approach. $F_{Current}$, $F_{Previous}$, and $F_{Previous2}$ are the values of the focus measure of the image at the current lens position, and at earlier lens positions, respectively; *down* is the number of consecutive decreasing steps including the most recent step; and *up* is the number of consecutive increasing steps.

$$
\begin{aligned}
ratio(x,y) &= \left(\frac{F_{Current}}{F_{Previous}} > \frac{x}{y}\right), \quad x = 1,\ldots,15, \;\; y = 8 \\
ratioI(x,y) &= \left(\frac{F_{Previous}}{F_{Current}} > \frac{x}{y}\right), \quad x = 2,\ldots,12, \;\; y = 8 \\
downSlope(x,y) &= \left(\frac{F_{Previous2}/F_{Previous}}{F_{Previous}/F_{Current}} > \frac{x}{y}\right), \quad x = 2,\ldots,12, \;\; y = 4 \\
upSlope(x,y) &= \left(\frac{F_{Current}/F_{Previous}}{F_{Previous}/F_{Previous2}} > \frac{x}{y}\right), \quad x = 2,\ldots,10, \;\; y = 4 \\
downTrend &= (F_{Current} \leq F_{Previous} \text{ and } F_{Previous} \leq F_{Previous2}) \\
upTrend &= (F_{Current} \geq F_{Previous} \text{ and } F_{Previous} \geq F_{Previous2}) \\
downOrFlatTrend &= (F_{Current} \leq (1.005 * F_{Previous}) \text{ and} \\
&\quad F_{Previous} \leq (1.005 * F_{Previous2})) \\
upOrFlatTrend &= (F_{Current} \geq (1.005 * F_{Previous}) \text{ and} \\
&\quad F_{Previous} \geq (1.005 * F_{Previous2})) \\
downhillCount &= \begin{cases} a & \text{if } down \leq 1 \\ b & \text{if } down = 2 \\ c & \text{if } down = 3 \\ d & \text{if } down \geq 4 \end{cases} \\
uphillCount &= (up \geq 1) \\
logDiff(x,y) &= \left(\frac{diff}{\log(F_{Previous})} > \frac{x}{y}\right) \quad x = 1,\ldots,8, \;\; y = 8 \\
&\quad \text{where } diff = \begin{cases} 0 & \text{if } F_{Current} \leq F_{Previous} \\ \log(F_{Current} - F_{Previous}) & \text{if } F_{Current} > F_{Previous} \end{cases}
\end{aligned}
$$

captured from the live preview stream once the lens is moved from one position to the next. The camera used in our experiments was a Canon EOS 550D/Rebel T2i.

In the second stage, we obtained the focus measurements and the correct labels for each focus position within each benchmark. In supervised learning, each instance in the data is a vector of feature values and the correct classification or label for that instance. In our approach, the class label is either "Fine", a single step of the lens, or "Coarse", a large step of the lens corresponding to eight single steps. Given a benchmark set of images, the squared gradient focus measure was applied to each jpeg image in the benchmark (see Figure 2 for an example). Each focus measurement was then labeled with either Coarse or Fine, depending on what was judged to be the best stepsize at that point if one were performing a sweep from near focus to far focus. For example, for the example focus measurement graph shown in Figure 2, if the current lens position is anywhere from position 30–86, the best stepsize to take would be a Coarse step (in order to step quickly through the lens positions), and from positions 87–113 the best stepsize would be a Fine step (in order not to miss the

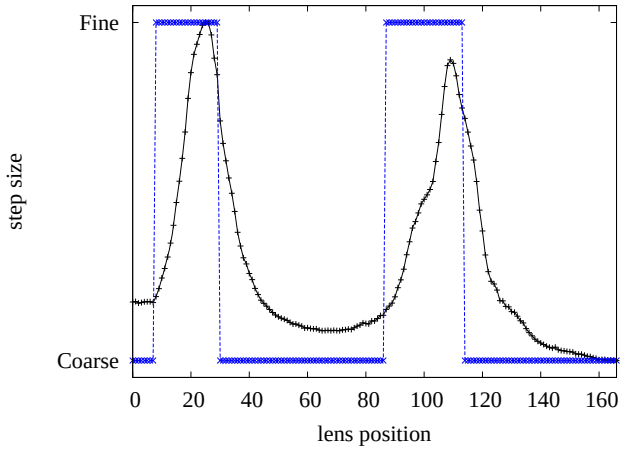


Fig. 2 Focus measures of images at each of the 167 lens positions for an example scene labeled with the best next step to take (a Fine step, or a Coarse step) when sweeping the lens from near to far (left to right in graph).

peak). The focus measurements were labeled in a semi-automated manner where an automatically generated labeling was then refined by hand to remove any anomalies due to noise.

In the third and final stage, we generated the actual machine learning data using a forward simulation of a sweep autofocusing algorithm. The input to the simulation was a set of labeled focus measurements for a benchmark. The algorithm starts at near focus and at each lens position until it reaches far focus it does the following: (i) outputs the values of the full set of sixty features (see Table 1) using the current values of $F_{Current}$, $F_{Previous}$, $F_{Previous2}$, *down*, and *up*; (ii) outputs the class label associated with that lens position; and (iii) steps forward the distance specified by the class label.

Several key techniques allowed us to greatly improve the quality of our data and the resulting efficiency and accuracy of our approach.

1. We separated the problem of learning a single heuristic for predicting the next stepsize into the problem of learning two heuristics: a heuristic for when the autofocus algorithm should transition from taking Fine steps to taking Coarse steps (i.e., predicting the next stepsize when the last step taken was a Fine step), and a heuristic for when to transition from taking Coarse steps to taking Fine steps (i.e., predicting the next stepsize when the last step taken was a Coarse step).
2. We added noise to the forward simulation. With some small probability p (in our experiments we used $p = 0.10$), the simulation will make a mistake either by taking a Coarse step, when the best stepsize would have been a Fine step, or vice-versa. The simulation is then repeated 10 times for each benchmark. We found that without the added noise, the heuristics that were learned were brittle: once

a mistake was made, they did not recover. With the added noise, the heuristics robustly recover from mistakes.

3. We balanced the data sets. A data set is balanced if the frequency of the classes is approximately equal. Imbalanced data sets can lead to poor predictive accuracy. In our case, the initial data was quite imbalanced. Consider the case where the forward simulation of the autofocus algorithm is taking Coarse steps and we are learning when to transition from taking Coarse steps to taking Fine steps. Most of the time the best next step is to continue to take Coarse steps, and only quite rarely to transition to Fine steps. To balance the data sets, we used the simple but effective technique of duplicating the instances from the minority class (Van Hulse et al, 2007).

We obtained a total of 22,794 and 36,580 instances for learning a heuristic when the last step taken was a Fine step and a Coarse step, respectively.

4.3 Feature selection

Once the data was collected but prior to actually learning the heuristics, the next step that we performed was feature selection. The goal of feature selection is to select only the most important features for constructing good heuristics. The selected features are then retained in the data and subsequently passed to the learning algorithm and the features identified as irrelevant or redundant are deleted. There are two significant motivations for performing this preprocessing step: the efficiency of the learning process can be improved and the quality of the heuristic that is learned can be improved (many learning methods, decision tree learning included, do poorly in the presence of redundant or irrelevant features (see Witten and Frank, 2000, pp. 231-232)).

Table 2 The features selected for learning a heuristic when the last step taken was a Fine step and when the last step taken was a Coarse step.

last step	features			
Fine	$ratio(8,8)$			
Coarse	$ratio(10,8)$	$ratio(11,8)$	$ratioI(9,8)$	
	$downSlope(9,8)$	$upSlope(8,4)$	$upTrend$	$logDiff(6,8)$

Many feature selection methods have been developed (see, for example, Guyon and Elisseeff (2003) and the references therein). To perform feature selection, we used the Weka (Version 3.6.9) open source machine learning software (Hall et al, 2009). In particular, we used Weka's best first search with the default parameters, a greedy hillclimbing method augmented with limited backtracking that searches forward starting from the empty set of features and adds features as long as the feature evaluator indicates improvement. The feature evaluator we used was the classifier subset evaluator, which evaluates a subset of features by constructing a decision tree classifier using the subset of features, using 10-fold cross-validation (see Hastie et al, 2009, pp. 241-249) to estimate the accuracy of the decision tree classifier, and finally

using the accuracy estimate as a figure of merit for the subset of features. For the construction of the decision tree classifier, we used the default settings with the exception that we set the minimum number of training instances at a leaf to 256 since, as noted in Section 4.2, lots of data was available. Table 2 shows the features that remained after selection. All of these features appeared in all 10 of the cross validation tests, an indication of their robustness.

4.4 Classifier selection

The next step is to actually learn the heuristics using all of the available data, where the data contains only the features that passed the selection step (see Table 2). To learn a classifier, we used Weka's (Hall et al, 2009) J48 implementation of Quinlan's C4.5 decision tree algorithm (Quinlan, 1993). We chose decision tree classifiers for learning the heuristics over other possible machine learning techniques because they are accurate, easy to understand, and efficient to evaluate. The software was run with the default parameter settings, with the exception that we again (as in feature selection) set the minimum number of instances at a leaf to 256 since lots of data was available and it resulted in much simpler trees.

As noted, the final decision trees were constructed using all of the available data. Algorithm 2 shows the final decision trees in algorithmic form, as would be incorporated into a sweep autofocus routine of a camera. Lines 1–2 correspond to the heuristic learned when the last step taken was a Fine step, and Lines 3–18 correspond to the heuristic learned when the last step was a Coarse step. The autofocus algorithm accepts an interval $[a, a+1, \ldots, b]$ over which to search, where a is the starting lens position, and returns the position of the maximum focus measure over the interval.

5 Experimental Evaluation

In this section, we empirically evaluate the effectiveness of our machine-learning-based (ml-based) heuristics. We compare against the Global search algorithm, the Fibonacci search algorithm, and Kehtarnavaz and Oh's (2003) rule-based heuristic. Recall that the Global search algorithm can be used to find all peaks and the Fibonacci search algorithm can be used to find the highest peak—provided the function is unimodal over the lens positions. Both Kehtarnavaz and Oh's rule-based heuristic and our ml-based heuristics were incorporated into a sweep focusing algorithm for finding the highest peak over the full range of lens positions for a lens (see Algorithm 1 and Algorithm 2, respectively). Following Kehtarnavaz and Oh (2003), in Algorithm 1 we used the squared gradient focus measure and we used 1, 3, and 10 steps for the *Fine*, *Mid*, and *Coarse* stepsizes, respectively. In our Algorithm 2 we used the squared gradient focus measure and we used 1 and 8 for the *Fine* and *Coarse* stepsizes, respectively, as these correspond to the stepsizes for Canon cameras.

As a test suite for comparing the algorithms, we used the same 25 sets of benchmark images that we used in data collection (see Section 4.2). There are a total of 4,303 images (23 of the benchmarks have 167 images; two of the benchmarks have

Algorithm 2: Machine-learning-based search algorithm for finding a maximum of a focus measure $\phi(p)$ over a set of focus positions $p \in \{a, a+1, \ldots, b\}$.

```
   input : Function φ(p) and interval [a,b]
   output: Return maximum of φ(p) over p ∈ {a,a+1,...,b}
   lastStep ← Coarse;
   F_Current ← φ(a); F_Max ← F_Current;
   F_Previous2 ← F_Current; F_Previous ← F_Current;
   p ← a + Coarse;
   while p ≤ b do
       F_Previous2 ← F_Previous;
       F_Previous ← F_Current;
       F_Current ← φ(p);
       if lastStep = Fine then
1          if ratio(8,8) = 0 then stepSize ← Coarse;
2          if ratio(8,8) = 1 then stepSize ← Fine;
       if lastStep = Coarse then
3          if ratio(10,8) = 0 then
4              if downSlope(9,8) = 0 then stepSize ← Coarse;
5              if downSlope(9,8) = 1 then
6                  if ratioI(9,8) = 0 then
7                      if logDiff(6,8) = 0 then
8                          if upSlope(8,4) = 0 then stepSize ← Coarse;
9                          if upSlope(8,4) = 1 then stepSize ← Fine;
10                     if logDiff(6,8) = 1 then
11                         if upTrend = 0 then stepSize ← Fine;
12                         if upTrend = 1 then stepSize ← Coarse;
13                 if ratioI(9,8) = 1 then stepSize ← Coarse;
14         if ratio(10,8) = 1 then
15             if downSlope(9,8) = 0 then
16                 if ratio(11,8) = 0 then stepSize ← Coarse;
17                 if ratio(11,8) = 1 then stepSize ← Fine;
18             if downSlope(9,8) = 1 then stepSize ← Fine;
       if F_Current > F_Max then F_Max ← F_Current;
       lastStep ← stepSize;
       p ← p + stepSize;
```

231 images). Recall that the our goal is to identify both the highest peak and all peaks in the focus measure across the lens positions. Thus, we compare the algorithms on three criteria: (i) the number of lens movements taken by an algorithm to sweep from near focus to far focus, (ii) whether the algorithm found the lens position corresponding to the highest peak in the focus measure, and (iii) whether the algorithm found all of the peaks in the focus measure. An algorithm found a peak if the lens was at that position during the course of the algorithm; an algorithm did not find a peak if the lens was stepped over that position by taking a larger stepsize that began before the peak and ended after the peak.

The Fibonacci and rule-based algorithms were run directly on the benchmark suite (see Table 3). To assess the ml-based heuristics, we used a variation of leave-one-out cross-validation. Cross validation methods are widely used for assessing per-

Table 3 Steps (lens movements) taken and peaks found by Fibonacci, rule-based, and machine-learning-based focusing algorithms using the squared-gradient focus measure. Peaks found is in the form *x*/*y*, where *x* is the number of peaks found and *y* is the total number of peaks. A red (dark) entry indicates that an algorithm did not find the lens position for which the focus measure was at a maximum. A yellow (light) entry highlights that an algorithm did not find all peaks in the focus measure. Global search takes 167 steps on each benchmark, except for the benchmarks Cat and Moon, where it takes 231 steps. The last column shows the speedup in steps of the proposed machine-learning-based algorithm over the previous rule-based algorithm.

	Fibonacci		rule-based		ml-based		
test benchmark	steps	peak	steps	peak	steps	peak	speedup
Backyard	12	1/1	75	1/1	54	1/1	28.0%
Bench	12	1/1	70	1/1	31	1/1	55.7%
Book	12	0/1	41	1/1	35	1/1	14.6%
Bridge	12	1/1	75	1/1	46	1/1	38.7%
Building1	12	1/1	67	1/1	39	1/1	41.8%
Building2	12	1/1	66	1/1	24	1/1	63.6%
Building3	12	1/1	67	1/1	30	1/1	55.2%
Cat	13	1/2	71	2/2	43	2/2	39.4%
Cup1	12	1/1	62	1/1	36	1/1	41.9%
Cup2	12	1/2	59	1/2	32	1/2	45.8%
Cup3	12	1/2	64	1/2	34	1/2	46.9%
Cup4	12	1/4	67	3/3	36	3/3	46.3%
Fabric	12	1/1	57	1/1	34	1/1	40.4%
Flower	12	1/2	66	2/2	41	2/2	37.9%
Interior1	12	1/1	74	1/1	55	1/1	25.7%
Interior2	12	1/4	77	3/4	46	3/4	40.3%
Lamp	12	1/4	72	3/4	42	4/4	41.7%
Landscape1	12	1/1	78	1/1	52	1/1	33.3%
Landscape2	12	1/1	75	1/1	46	1/1	38.7%
Landscape3	12	1/1	71	1/1	41	1/1	42.3%
Moon	13	0/1	87	1/1	38	1/1	56.3%
Screen	12	1/2	43	1/2	62	2/2	−44.2%
Snails	12	1/1	57	1/1	37	1/1	35.1%
StillLife	12	0/1	64	1/1	37	1/1	42.2%
Vase	12	1/1	52	1/1	31	1/1	40.4%

formance in machine learning (see Hastie et al, 2009, pp. 241-249). For *each* of the 25 benchmarks in turn, we performed the following: (i) set aside the current benchmark, call it the *test* benchmark; (ii) collect the machine learning data (as in Section 4.2), but using only the remaining 24 benchmarks, omitting the test benchmark; (iii) perform feature selection (as in Section 4.3), but using only the data that omits the test benchmark; (iv) perform classifier selection (as in Section 4.4), but again using only the data and features selected using the machine learning data that omits the test benchmark; and (v) incorporate the learned heuristics into an algorithm and evaluate on the test benchmark.

The goal of the evaluation procedure—in our case, a variation of leave-one-out cross validation—is to assess the generalization performance of the heuristic; i.e., how well will the heuristic perform in practice on new data. The decision trees that are constructed using a subset of the data during the evaluation procedure are only used to estimate the generalization performance of the decision tree learned from *all* of the data and presented in Algorithm 2, and otherwise are not retained.

Table 3 summarizes the results of the empirical evaluation. On these benchmarks, the Fibonacci algorithm (Kiefer, 1953) was fast but inaccurate, often missing the highest peak and sometimes not finding any peak (due to small amounts of noise in the focus measurements). The rule-based algorithm (Kehtarnavaz and Oh, 2003) always found the highest peak and missed a lesser peak on five of the benchmarks. Our ml-based algorithm also always found the highest peak and missed a lesser peak on only three of the benchmarks. Thus, our ml-based heuristic is somewhat more accurate than the rule-based heuristic. However, the main advantage of our ml-based heuristic is in speed: it is faster on 24 of the benchmarks and in the one case where it is slower, it is more accurate. The ml-based heuristic is 39.7% faster on average over all 25 benchmarks and 41.3% faster on average if one excludes the benchmark where it is more accurate.

The question arises as to how the current proposal compares to autofocusing on commercially available cameras. Fortunately, the question can be partially answered albeit indirectly. Gamadia and Kehtarnavaz (2009) present a real-time implementation of a modification of the rule-based algorithm on a Texas Instruments DM350 processor, where the rule-based algorithm has been modified to stop at the nearest peak (Peddigari et al, 2005). As is the case with the camera's autofocus algorithm running on the camera's on-board processor, the DM350 processor then controls the lens directly with no communication delays. In Gamadia and Kehtarnavaz's (2005) experimental evaluation, it is shown that the real-time implementation of the rule-based algorithm is able to perform nearest peak autofocusing faster than commercial cameras. Speed-ups of from 27.6% to 84.0% are reported for five common point-and-shoot commercial cameras and both wide and zoom modes (see Gamadia and Kehtarnavaz, 2009, Table 2). Thus, given that our algorithm performs about one-third fewer steps on average than the rule-based algorithm and that it is the lens movements themselves that are the bottleneck—the time taken to calculate the next step to take is negligible in comparison—there is good reason to believe that our proposal will be faster still than these commercial cameras.

6 Conclusion

The speed and accuracy of a digital camera's contrast-based autofocus algorithm are crucial to user satisfaction. Previous work has proposed a hand-crafted rule-based autofocus heuristic to find the peak focus (Kehtarnavaz and Oh, 2003). We showed that supervised machine learning techniques can be used to construct heuristics that out-perform the state-of-the-art hand-crafted heuristic. We gathered an extensive set of benchmark images that covered a range of common photography settings. Offline simulation was then used to construct the machine learning data and decision tree heuristics were induced from the data. In our experiments, the machine-learning-based algorithm was significantly faster—reducing the number of steps needed to focus by 63.6% in the best case and by 39.7% on average—as well as more accurate.

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