Evaluation of Sharpness Measures and Search Algorithms for the Auto-Focusing of High Magnification Images

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ABSTRACT

Digital imaging systems with extreme zoom capabilities are traditionally found in astronomy and wild life monitoring. More recently, the need for such capabilities has extended to long range surveillance and wide area monitoring such as forest fires, airport perimeters, harbors, and waterways. Auto-focusing is an indispensable function for imaging systems designed for such applications. This paper studies the feasibility of an image based passive auto-focusing control for high magnification systems based on off-the-shelf telescopes and digital cameras/camcorders, with concentration on two associated elements: the cost function (usually the image sharpness measure) and the search strategy. An extensive review of existing sharpness measures and search algorithms is conducted and their performances compared. In addition, their applicability and adaptability to a wide range of high magnifications (50×~1500×) are addressed. This study builds up the foundation for the development of auto-focusing schemes with particular applications to high magnification systems.

Keywords: Sharpness measure, auto-focusing, high magnification, wide area surveillance

1. INTRODUCTION

Wide area surveillance and remote monitoring require cameras with large zoom capabilities, usually in the magnitudes of hundreds or even thousands. To build a high magnification imaging system from off-the-shelf components, we studied several system setups based on various scopes, eyepieces, and digital cameras/camcorders [1]. For such system to be applicable to real-time tracking scenarios, it is necessary and crucial to maintain the moving target in focus. Manual controllability provided by the scopes is no longer sufficient. To facilitate the remote and automatic control of high magnification imaging systems, the auto-focusing capability is to be integrated.

A variety of auto-focusing methods exist in both the academic literature and the commercial marketplace. Image based passive auto-focusing algorithms are selected for study primarily because they require no additional devices, such as a range finding sensor or a split prism. In image based passive approaches, the system measures the degree of in-focus (criterion function) of the images collected at various focus locations and finds the focus position where the corresponding in-focus measure is maximized (search strategy). The criterion function and search strategy are two elements paramount for a successful auto-focusing algorithm.

One type of commonly used criterion functions is known as the sharpness measure. In addition to some well known sharpness measures, such as the Tenengrad and Laplacian measures [2], edge based sharpness measures [3-5], where local characteristics of strong edges are explored, have emerged in recent years. This paper looks into various sharpness measures published to date and compares their performances using high magnification images. Such images suffer from substantial blur and low signal to noise ratios.

This paper also reviews existing search algorithms, such as the famous Fibonacci search [2], and the more recently developed rule-based search [6], a variable step size algorithm. The performance of each search method in conjunction with different sharpness measures is examined in the following aspects: accuracy, computational complexity (the number
of iterations and motor steps traveled before convergence), and stability (robustness to image noise and sensitivity to algorithm parameter selection).

The remainder of this paper is organized as follows. The existing sharpness measures and search algorithms are studied in sections 2 and 3, respectively. Experimental results are demonstrated and compared in section 4. Section 5 concludes this paper.

2. SHARPNESS MEASURES

Sharpness measures have been traditionally divided into 5 categories [7]: gradient based, variance based, correlation based, histogram based, and frequency domain based methods. With the development of practical edge detectors, edge based sharpness measures have attracted increasing attention. Meanwhile, sharpness measures using wavelet transform also came into view. Based on the categories described in [7], modifications are made to incorporate these newly proposed measures. Our classification includes the following 5 categories: gradient based, correlation based, statistics based (combining variance and histogram based methods), transform based (including frequency and wavelet domain based methods), and edge based methods.

2.1. Gradient based measures

Grey level differences among neighboring pixels provide a reasonable representation of an image’s sharpness. Image gradient obtained by differencing or using high pass filters are abundant in literature. Different forms of gradients can be used [7]: (1) the absolute gradient defined as $S = \sum_{M} \sum_{N} |I(x+1, y+1) - I(x, y)| + |I(x+1, y) - I(x, y)|$, (2) the squared gradient given by $S = \sum_{M} \sum_{N} \sqrt{I(x+1, y+1) - I(x, y)}^2 + |I(x+1, y) - I(x, y)|^2$, and (3) the maximum gradient formulated as $S = \sum_{M} \sum_{N} \max\{I(x+1, y+1) - I(x, y), |I(x+1, y) - I(x, y)|\}$, where $I(x, y)$ represents the image intensity, $M \times N$ denotes the total number of image rows (columns), and $n$ is the differencing step. The absolute gradient with $n=1$ is also called the sum modulus difference (SMD) measure and the case with $n=2$ is commonly referred to as the Brenner measure [7].

The most well known measure based on high pass filters is the Tenengrad measure [2]. The Tenengrad measure is given by $S = \sum_{M} \sum_{N} (I_{x}^2 + I_{y}^2)$, while $I_{x}^2 + I_{y}^2 \geq T$, with the horizontal and vertical gradients, $I_{x}$ and $I_{y}$, obtained using the Sobel filters and $T$ is a threshold. The Laplacian filter is another popular choice [2], where the sharpness is defined by $S = \sum_{M} \sum_{N} |L|$, while $|L| \geq T$ with $L(x, y) = I(x, y) * h(x, y)$ and $h = \begin{bmatrix} 1 & 4 & 1 \\ 4 & -20 & 4 \\ 1 & 4 & 1 \end{bmatrix}$. Choi et al. utilized a linear combination of multiple median filters, referred to as the frequency selective weighted median (FSWM) filter [8].

2.2. Correlation based measures

Correlation evaluates the dependency among neighboring pixels, which provides another practical way to quantize image sharpness. In literature [7], some of the sharpness measures simply compute one sample of the autocorrelation function:

$$S = \sum_{x=1}^{M-1} \sum_{y=1}^{N-1} I(x, y)I(x+1, y) - \sum_{x=1}^{M-2} \sum_{y=1}^{N-2} I(x, y)I(x+2, y).$$

More evolved measures depend on multiple samples and define quantities such as the area and the height of the central peak of the correlation function [9, 10].
2.3. Statistics based measures

Sharp images usually involve scattered grey levels in a large dynamic range, suggesting a large variance. Two widely recognized variance based sharpness measures are the grey level amplitude and variance. The grey level amplitude, also referred to as the absolute central moment (ACM) measure [11], is defined as

\[ S = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} |I(x, y) - \bar{I}|, \]

where \( \bar{I} \) is the mean grey level. The grey level variance follows the traditional definition:

\[ S = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} (I(x, y) - \bar{I})^2 \]

[7]. The ratio between the high and low order Chebyshev moments was also used to describe the perception of image sharpness [12].

Several sharpness measures are derived from the image histogram. The most straightforward definition is the difference between the maximum and minimum grey levels. Another popular choice is the image grey level entropy [7]. Krotkov et al. also proposed a measure using the histogram of local variations, namely the local histogram variation measure [2].

2.4. Transform based measures

For frequency domain based sharpness measures, the image is first transformed into the frequency domain usually via a Fourier transform (FT) or a discrete cosine transform (DCT). The sharpness measure is then computed based on these transformed coefficients or their distributions. The fast Fourier transform (FFT) sharpness measure is defined as

\[ S = \sum_{(u,v)\in D} |\text{Mag}(u,v) \times \text{Angle}(u,v)| \]

[13]. The sum of the amplitudes of the frequency components within a predefined window, \( S = \sum_{(u,v)\in D} \text{Mag}(u,v) \), was also used as a sharpness measure by Batten [9].

Besides point based definitions, some measures explore the statistical information contained in the frequency domain. The multivariate kurtosis, derived from the distribution of 2D FT coefficients, was employed as a sharpness metric [14]. Kristan et al. proved that the maximum entropy in the frequency domain coincides with the maximum image spatial sharpness and proposed an entropy based measure [15, 16]. Wang et al. observed that image edges result in strong local phase coherence in the wavelet domain while blurred local structures cause loss of such phase coherence [17]. Therefore, the errors in phase prediction in turn indicate the degrees of image sharpness.

2.5. Edge based measures

Edge based measures make use of the edge components, which are primarily responsible for the visual perception of image sharpness. Li [3] defined an ideal 2D step edge as

\[ I(x, y) = b + c \left[ 1 + \text{erf} \left( \frac{x \cos \theta + y \sin \theta}{\sqrt{2w}} \right) \right], \]

where \( c, \theta, \) and \( w \) represent the contrast, orientation and scale respectively, and \( \text{erf}(\cdot) \) denotes the error function. The scale \( w \) describes the width of the edge transition, whose average value yields a reasonable indicator of image sharpness. The proposed algorithm elegantly avoids estimating edge orientation and provides a neat solution to edge characterization. However, the difficulties in detecting and isolating step edges still remain. A filter bank, adjusted to various edge orientations, was used by Dijk et al. to detect the average edge width [4].

As an improvement over the global kurtosis sharpness measure [14], Caviedes et al. proposed a local kurtosis sharpness measure based on detected edges [5]. Compared with other edge based algorithms, the local kurtosis measure handles different types of edges in the same fashion and avoids the difficulty in distinguishing step and line edges. In parallel, Lin et al. made use of the coefficients of the detected edge points in the wavelet domain [18].
3. SEARCH ALGORITHMS

There exist two elementary groups of auto-focusing methods, referred to as active and passive auto-focusing. In active auto-focusing, range finding sensors are commonly used to determine the distance between the target and the observation camera. Passive auto-focusing methods can be further divided into two categories: device based and pure image based. Device based passive auto-focusing approach integrates additional devices to achieve auto-focusing, such as a stereo matching unit or a split prism. Image based approach does not require extra equipment. The best focus location is obtained based on the image sequences collected at sampled focus positions. We are interested in image based passive auto-focusing methods primarily because of their simple configuration in hardware.

Depth from defocused images represents one major direction in image based passive auto-focusing algorithms [19]. The distance between the target and the camera (depth) is estimated from several defocused images. The degree of the blur is characterized as the variance of a Gaussian kernel, which can be evaluated from the defocused images. Target depth is expressed as a function of these variances and can be estimated when these variances are available. Afterwards, from the relationship between target depth and camera focus, the desired focus position can be determined. Since considerable amount of blur comes from high magnifications in our system, the simple relation between the blur and target distance is not entirely valid. For this reason, the feasibility of using this type of methods in high magnification systems remains questionable.

In the second main branch of image based passive auto-focusing algorithms, the optimal focus is found by searching for the focus location that yields an image with the highest sharpness measure. Various search strategies are proposed. The most straightforward method is the global search. The peak position is obtained by scanning through all focus positions in a unidirectional manner. It is only applicable to cases with narrow focus range.

The Fibonacci search is the most well known search algorithm [2]. The Fibonacci search successively narrows the search interval until its size equals a given fraction of the initial search range. It guarantees that the maximum of the criterion function is found within a known number of iterations depending only on the dynamic focus range.

In the binary search, the criterion function is sampled at two locations and their difference is computed [2]. If the difference is negative, the next move follows the opposite direction. Given the unimodal shape of the criterion function, the binary search can converge to the best focus location at a fast speed provided heuristic choices of the step magnitude. Developed from the basic binary search, the hill-climbing search divides the procedures into two stages: out-of-focus region searching (OFRS) and focused region searching (FRS) [20]. A number of hill-climbing algorithms have been proposed with modifications regarding step size selection, termination criteria, search window, etc [20, 21].

Given these basic search algorithms, variations are introduced for a faster and more accurate focus search. Lee et al. employed different sharpness measures for coarse and fine focus search stages [22]. In the coarse search stage, measures with low computational cost and low sensitivity to sidelobes, such as variance based measures, are used. Gradient based measures, for instance the Tenengrad measure, are then used for the fine search.

Subbarao et al. focused on the selection of a suitable focus measure and applied function fitting for a faster convergence [19]. In the fine search stage, image sharpness is evaluated at three focus locations. These samples are then fitted into a quadratic or a Gaussian function. The position where the fitted curve achieves the maximum is considered as the focused position.

To avoid the back-and-forth motor motion required by the Fibonacci search, Kehtarnavaz et al. proposed a sequential search algorithm, referred to as the rule-based search (RS), where the step size is varied according to the distance from the best focus location [6].

Special patterns, such as the radial test pattern, were used to calibrate the best focus position for applications with a fixed distance between the target and the camera [23]. The best focused image should have the smallest blurred region in the middle of the test image and hence the smallest equivalent radius. Lin et al. applied the circular Hough transform to determine the radius of the center blurred image, based on which the best focus location was obtained.
4. EXPERIMENTAL RESULTS

4.1. Comparison of sharpness measures

The performances of various sharpness measures are evaluated using low and high magnification sequences. The low magnification sequences are collected by a Canon A80 camera with an optical magnification of $3\times$. The high magnification sequences are collected by a compositing imaging system based on a Celestron telescope (GPS 11) and a Sony camcorder (TRV730). The achievable system magnification varies from $50\times$ to $1800\times$.

4.1.1. Low magnification sequences

Four representative sequences, referred to as the resolution chart (RC), Hello-Kitty (HK), license plate (LP), and man’s face (MF) sequences, are collected at intervals of 3 focus motor steps covering a focus range of 0.2m to infinity (a total of 60 images per sequence). Other camera configurations, such as zoom, iris, shutter speed, and exposure compensation, are kept unchanged. The indoor sequences study the influence of strong image edges. The RC sequence has dense and strong edges, while in comparison, the HK sequence has scattered edges of lower contrast. The outdoor sequences represent two typical applications in long range surveillance: highway patrol (LP) and public area monitoring (MF). In the interest of space, only the experimental results of the RC and LP sequences are discussed. Similar observations apply to the remaining sequences.

Figures 1 and 2 illustrate sample images from the RC sequence and the resulting sharpness measures, respectively. For clear presentation and according to their performances, the tested sharpness measures are divided into three groups. The first group includes sharpness measures such as SMD, Tenengrad (Ten), Laplacian (Lap), FSWM, and ACF, the performance of which exhibits a sharp peak centered at the best focus position. As the camera’s focus moves away from the best focus position, the output drops rapidly and then saturates. Sharpness measures in this group show the best performance. Sharpness measures, such as frequency entropy (FE), local Kurtosis (LK), edge area (EA), and edge width (EW), belong to the second group, where a wider peak with gradual slopes is observed, indicating a slightly degraded performance. Figure 2(c) depicts the performance of entropy, gray level variance (GrayVar), and local histogram variation (HistVar) measures. There exist noticeable zig-zag’s suggesting an increased noise level. Moreover, the centers of the entropy and HistVar measures drift away from the correct focus position. The measures in this group yield an overall inferior performance.

As to the outdoor LP sequence (Figures 3 and 4), we have similar observations with one exception: the FE measure, the performance of which is improved and resembles the performance of gradient based measures.

4.1.2. High magnification sequences

The Celestron lens’s existing focus control features a manually operated control knob requiring 40 turns to cover the complete focus range. To automate it, we coupled the control to an Animatics SmartMotor through a gear drive of our own design. When converted to motor steps and normalized to the minimum resolution, the dynamic range is -200 to 200 motor steps. A total of 400 frames is collected at these motion steps. Various system magnifications are used: 70×, 100×, 245×, 500×, and 1500× to provide a detailed and complete performance comparison. At each sampled magnification, two sequences are collected, one with strong and clustered edges such as the brick walls (BW) sequence and the other with scattered and low contrast edges such as the men’s face (MFH) sequence. Figure 5 shows sample images from the MFH sequence at a system magnification of 70× and with a target distance of 65m.
Figure 1 Sample images from the RC sequence with focus at (a) 0.2m, (b) best focus, and (c) infinity. Camera zoom: 3x. Target distance: 2m.

Figure 2: Sharpness measures of the RC sequence. (a) Group A including gradient based, correlation based, and some transform based measures, (b) group B including some transform based and edge based measures, and (c) group C including statistics based measures.

Figure 3 Sample images from the LP sequence with focus at: (a) 0.2m, (b) best focus, and (c) infinity. Camera zoom: 3x. Target distance: 2m.

Figure 4 Sharpness measures for the LP sequence: (a) group A including gradient based, correlation based, and some transform based measures, (b) group B including some transform based and edge based measures, and (c) group C including statistics based measures.
Figure 5 Sample images from the MFH sequence (system magnification: 70×, target distance: 65m): (a) the first frame, (b) the frame with best focus, and (c) the last frame.

When applied to high magnification sequences, the performances of edge based measures deteriorate substantially since no sufficient strong edges are available due to degradations from air turbulence and limited optical details. Therefore, in order to maintain a reasonable response of the sharpness measure, we limit our consideration to three types of sharpness measures: gradient based, correlation based, and transform based measures.

As mentioned before, high magnification imaging systems suffer from degradations caused by air turbulence and limited details and light collected by the scope. As a consequence, the resulting images are often blurred and of low contrast, which is responsible for the significantly increased noise level in the sharpness measures. As the system magnification increases, more severe blur is introduced and the noise level increases accordingly. Furthermore, some sharpness measures cannot keep the required unimodal shape in such conditions. Multiple local maxima are observed. When the system magnification exceeds 1500×, for our tested sequences, only three sharpness measures (SMD, Tenengrad, and FE) are able to produce responses with reasonable shapes. With further increase in system magnification, image blur from high magnification becomes overwhelming. It is difficult for the sharpness measures to differentiate between the magnification blur and the out-of-focus blur.

Figure 6 Performance comparison across various sharpness measures for the BW sequences with a system magnification and an approximate target distance of: (a) 70×, 70m; (b) 100×, 100m; (c) 245×, 200m; (d) 500×, 300m; and (e) 1500×, 350m.
4.1.3. Summary and conclusions

A detailed performance comparison of existing sharpness measures is conducted using low and high magnification sequences. According to our experimental results, the characteristic behaviors of various sharpness measures can be summarized as follows.

(1) Gradient based measures yield a performance closest to the ideal response and more importantly their performances are robust to degradations introduced by high magnification. However, their output drops rapidly as the focus moves away from the best position and saturates, resulting in a large portion of flat response disregarding the changes in the camera’s focus. Given an initial focus position in the saturation region, it is difficult to determine which direction leads to an increased image sharpness.

(2) The performance of the correlation based measures is comparable to that of the gradient based measures. The decreasing/increasing slope is adjustable by choosing different window sizes. With a smaller window size, the response is relatively sharp and narrow similar to that of the gradient based measures, while measures with a larger window size produce wide peaks and gradual slopes, as shown in Figure 7. This feature can be used to balance two criteria during the successive focus search: precise location and easy direction initialization.

(3) Statistics based measures carry out global operations, such as computing image variance and histogram, and neglect the local information around image edges, which is responsible for their inferior performances.

(4) As to the measures defined in transform domain, their performance falls in between the gradient based and statistics based measures. The associated computations depend on the transform used. Measures based on FT and DCT share comparable computations to the correlation function based measures.

(5) Edge based measures yield comparable performances as transform based measures. However, their computational complexity substantially deteriorates their merits. In addition, it is difficult to detect strong edges in a blurred high magnification image. Thus its applicability to high magnification images remains questionable. Table 1 summarizes the comparison.

4.2. Comparison of search algorithms

To evaluate the performance of various search algorithms, each in conjunction with different sharpness measures, we carried out the following experiments. Images are collected at uniformly distributed camera focus positions and the relative sharpness measures are computed as discussed in section 4.1. A search algorithm is then applied to locate the best focus position. Ideally, the estimated focused position should correspond to the focus position with the maximum
sharpness value. Any difference between them is the estimation error and the size of the estimation error describes the accuracy of the search algorithm. Another performance criterion is the computational complexity, which measures the number of iterations and motor steps traveled before the optimal focus is obtained. These two factors (iterations and motor steps) determine the speed of the search algorithm. They are often closely related, with a large number of iterations suggesting a large number of motor steps. An exception is the Fibonacci search, where a small number of iterations is guaranteed, but where a large number of motor steps often results from the algorithm’s back-and-forth search behavior.

We limit our consideration to four types of sharpness measures excluding the statistics based measures for their low performance. Various search algorithms are implemented, including the binary search (BS), Fibonacci search (FS), and rule-based search (RS). In our BS implementations, the step size is halved when the difference in sharpness measure changes sign. In addition, quadratic function fitting is applied to the fine search stage, following the coarse search based on BS and FS. The resulting algorithms are referred to as BF and FF, respectively. Also implemented is one example of the hill-climbing search (HC) scheme [20].

Figure 8 compares the performances across various sharpness measures and search algorithms based on errors in detected focus position, the number of iterations, and the number of motor steps. As for accuracy, the Fibonacci, hill-climbing, and rule-based searches result in the best performance. However, the performance of the hill-climbing search is sensitive to the parameters used, such as the step size and thresholds. These parameters must be selected carefully, especially for noisy applications.

<table>
<thead>
<tr>
<th>Sharpness Measures</th>
<th>Advantages</th>
<th>Disadvantages</th>
<th>Computational Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gradient based</td>
<td>Quick response, Applicable to high magnification images</td>
<td>Large portion of saturation region</td>
<td>$O(MN)$</td>
</tr>
<tr>
<td>Statistics based</td>
<td>Low accuracy and noisy response</td>
<td></td>
<td>$O(MN)$</td>
</tr>
<tr>
<td>Correlation based</td>
<td>Quick response, Applicable to high magnification images, Response slope is adjustable</td>
<td>Slightly increased computations</td>
<td>Sample $O(MN)$</td>
</tr>
<tr>
<td>Transform based</td>
<td>Applicable to high magnification images</td>
<td>Slightly increased computations</td>
<td>Function $O(MN\log(MN))$</td>
</tr>
<tr>
<td>Edge based</td>
<td>Computational complexity, Separation of strong edges, Not applicable to high magnification images</td>
<td></td>
<td>Depends on the edge detection algorithm used</td>
</tr>
</tbody>
</table>

Figure 8 (a) Comparison across sharpness measures and search algorithms for the LP sequence. (a) Estimation error expressed in motor steps (the estimation errors for RS, HC, and FS are zeros). (b) The total number of iterations used before obtaining the optimal focus position (the smallest number of iterations: FF and HC). (c) The total number of motor steps traveled before obtaining the optimal focus position (the smallest number of motor steps: RS, BF and HC).

With the Fibonacci search, the number of iterations is fixed for a given focus range. However, the Fibonacci search involves the most back-and-forth motions and therefore the most motor steps. Although the rule-based search and the binary search need a similar number of iterations, the rule-based algorithm involves only unidirectional movements and
hence requires fewer motor steps. The use of function approximation avoids unnecessary iterations during the fine search stage, thereby reducing the total number of iterations and motor steps.

Figure 9 demonstrates the experimental results using high magnification sequences. Due to magnification blur, more noise appears in the resulting sharpness measures, leading to obviously increased estimation errors. The binary search and the hill-climbing search, inherently sensitive to image noise and magnification blur, present the most performance degradation.

As a conclusion, we rank the studied search algorithms based on our experimental results. These search algorithms are compared under three criteria: accuracy, computational complexity described by the number of iterations and motor steps, and stability (sensitivity to image noise, algorithm parameter selection, and magnification blur). Overall, the rule-based search and the Fibonacci search with function fitting generate the best performance. In our real-time auto-focusing system, extra attention is paid to the number of motor steps, since our system has a larger focus range compared to traditional low magnification imaging systems. Therefore, the rule-based search algorithm appears to be the most promising candidate.

Table 2 Comparison of studied search algorithms. Rank 3 represents the best and rank 1 the worst.

<table>
<thead>
<tr>
<th></th>
<th>Accuracy</th>
<th>Iterations</th>
<th>Motor steps</th>
<th>Stability</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>RS</td>
<td>5</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>10</td>
</tr>
<tr>
<td>BS/BF</td>
<td>1</td>
<td>1/2</td>
<td>2/3</td>
<td>1/1</td>
<td>5/7</td>
</tr>
<tr>
<td>HC</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>FS/FF</td>
<td>3</td>
<td>2/3</td>
<td>1/1</td>
<td>3/3</td>
<td>9/10</td>
</tr>
</tbody>
</table>

4.3. Auto-focusing in real-time high magnification imaging

From the experimental results discussed in the previous sections, gradient based sharpness measure (Tenengrad) and the rule-based search algorithm are used for real-time auto-focusing in our high magnification system. Figure 10 shows sample images from the MFH sequence collected at a system magnification of 70x. Figure 11 depicts the sampled focus positions and the corresponding sharpness measure values. Given a starting point within ±100 motor steps of the peak region and with a frame rate of 7.2 frames/sec, our algorithm can precisely detect the optimal focus position within 2 seconds.
Based on raw images and a single sharpness measure, our auto-focusing algorithm works well for a system magnification of up to 500×. Further increases in magnification result in severely blurred images which undermine the ability of the sharpness measures to produce smooth and unimodal curves. Image pre-processing and the use of a combination of two types of sharpness measures are possible solutions.

5. CONCLUSIONS

For the purpose of long range surveillance and wide area monitoring, a high magnification imaging system (zoom capability of 50× to 1800×) was designed and built based on an off-the-shelf telescope and a digital camcorder. For this system to be applicable in real-time scenarios, image based passive auto-focusing mechanism was added. In this paper, we concentrated on two important components of such auto-focusing algorithms: the cost function (image sharpness measure) and the search strategy. We studied and compared the performances of various sharpness measures and search algorithms with focus on high magnification sequences. Based on our experimental results, gradient based sharpness measures and the rule-based search algorithm generated the best performance considering accuracy, computational complexity, and stability and were selected for real-time auto-focusing implementation.

REFERENCE: