A New Non-Contact Automatic Inspection Method for Micro-Structures

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This paper presents a new non-contact, non-destructive method for automatic inspection of microstructures. A piezoelectric actuator is used to vibrate the devices under inspection. The frequency of the vibrations is swept within an interval including the resonance frequency of the parts. A microscope camera is used to monitor the vibrations of the structures. At resonance, functional devices undergo large oscillations and are seen as a blur on the camera. Two image processing algorithms were used to measure the degree of blurriness from the camera images, namely, QuadTree segmentation and Otsu’s adaptive thresholding method. Using the QuadTree segmentation method, blurriness is detected from a drop in the count of image partitions. Using Otsu’s adaptive thresholding method, blurriness is detected from an increase in the count of white pixels in the
binarised image. In both cases, by setting a threshold on the number of partitions (white pixels), resonant parts can be distinguished from broken ones. Experimental tests proved the effectiveness of the proposed method, and indicated the feasibility of its application in real time plant environment. To the authors’ knowledge, this is the first fully automated quality control method for microstructures based on the analysis of their resonance vibrations.

**Keywords:** micromanufacturing, microgrippers, quality control, machine vision, image segmentation, adaptive thresholding.

1 Introduction.

The ongoing trend towards miniaturisation has had an important impact in areas as mechanics, electronics, microfluidics, medicine, biological engineering, and IT. In the manufacturing field, the need to build and assemble complex devices and parts in the micro- (sometimes nano-) scale has brought a completely new range of challenges. Devices composed of elements made of different materials have often to be fitted together with micrometre or even sub-micrometre precision. This task is complicated by the minute and often fragile nature of the parts, and the delicate build-up of the assembly.

At the end of the manufacturing process, the integrity and functionality of the products needs to be inspected. It is of crucial importance to recognise faulty devices prior packaging, since **packaging costs often exceed the overall production costs**. This paper describes a novel automatic technique for visual inspection of the functionality of electrostatic microgrippers.
Figure 1 shows the type of device considered in this study. The FT-G FemtoTools microgripper is an extremely miniaturized tool for handling micron-sized samples. It is mounted on a printed circuit board (PCB) where the control and read-out electronics are placed. This kind of microgripper has been used for many different applications such as sample handling in scanning electron microscopes, micro- and nano-assembly, micro-factories, sample preparation in biological and biomedical research, single cell handling, and material science.

During the assembly process, the microgripper is placed on the PCB. The position is manually adjusted by sliding the device into the right location with the help of a stereo microscope. Once the correct position has been achieved, the gripper is fixed permanently using epoxy glue, and manually wire-bonded to the PCB contact pads.

Quality control is needed to check that the parts are not broken, are assembled within the given tolerances, and are functional. This study is concerned with the automatic inspection of the functionality of the gripper’s arms. This task was up to now carried out by human inspectors using a microscope. Manual inspection requires close and time-consuming inspection of the parts. Moreover, some defects (e.g. tiny cracks in the microstructure) are hard to see. Other defects can not be detected visually, and need functional testing of the elements.

This paper presents a non-contact, nondestructive automatic inspection technique to detect broken and defective elements. The proposed method uses a piezoelectric actuator to elicit small vibrations of the arms. At resonance frequency, these vibrations become larger and can be seen using a microscope. Defective parts don’t vibrate accordingly, and can be identified using standard image processing techniques. The proposed inspection technique is a major breakthrough in the
inspection of microstructures, since it permits the detection of all types of fabrication defects.

Section 2 presents the visual inspection system; Section 3 surveys the literature on related inspection procedures. Section 4 describes the machine vision algorithms. Section 5 presents the experimental results of the application of the proposed methods. Section 6 concludes the paper and outlines the directions of further work.

2 Visual inspection system.

Visual inspection is one of the most common and effective quality control methods for micro-electro-mechanical systems. However, as mentioned in the introduction, there are defects that can not be identified by simple visual inspection. For example, it is not possible to verify that the mechanical part of the microgripper is fully released from the wafer substrate and can freely move, or that the stiffness of the elastic structures is within tolerances.

The proposed inspection procedure was developed within the EU FP6 Hydromel Project which aimed at the development of new production technologies for micro-devices using ultra-precision engineering techniques [1]. It was proposed by Femtotoools GmBH, the mechanical rig was realized by the Swiss Federal Institute of Technology, Zuerich (ETHZ), and the image processing algorithms were developed at Cardiff University. A piezoelectric actuator is used to apply a vibration signal to the microgripper under inspection, and the deflections of the arms are monitored via a microscope camera. The test is performed under vacuum, in order to eliminate damping effects that would limit the movement of the elastic structures. The actuation signal can be sinusoidal or any other shape. The amplitude of the vibrations of the
piezoelectric actuator is small (in the sub-micrometre scale) and is not visible via the camera. The frequency of the vibrations is swept across a pre-defined interval.

The arms of the gripper can be thought of as spring-damper systems. When they are vibrated at resonance frequency, the width of their oscillations increases manifolds and reaches several micrometres. These large deflections are visible via the microscope camera. Due to the high frequency of the vibrations, the resonating structures are seen as a blur.

Under vacuum, the resonance frequency of the arms depends only from their mass and elastic properties (i.e. spring coefficient). The presence of a defect alters the elastic properties of the microstructures and thus their resonance frequency. As a consequence, damaged parts are not seen as a blur at the expected frequency of vibration. This principle is used to detect defective parts.

The interval of frequencies that is scanned by the piezoelectric actuator is set to contain those values at which functional parts are expected to resonate. If no large deflections (i.e. blurring) of the components are seen across the frequency spectrum of the vibrations, it can be assumed that the microstructures under examination didn’t resonate and are thus defective. Namely, one of the following cases applies:

- The elastic microstructure is damaged (broken flexures).
- The mass or the stiffness of the microstructure is not within the tolerance.
- The microstructure is not released from the base substrate.
- A defect in the microstructure prevents its deflection.

It is important to notice that the last three kinds of defects are not detectable using standard visual inspection techniques. Figure 2 illustrates the prototype of
the proposed inspection system. The inspection rig is composed of the following elements. A vacuum chamber (1) with a transparent top cover (3) where the assembled PCB and gripper are placed for inspection. A feed-trough (2) that allows the electrical wiring of the components inside the chamber. A piezoelectric actuator composed of a computer-controlled frequency generator with a **SVR 150 3bip, Piezomechanik GmbH** high-voltage amplifier (4) that is used to produce the vibration signals. The gripper (5) which is placed on the piezoelectric actuator. The **vision equipment is composed of a gray-scale Basler 602fc camera mounted on an A-Zoom New technology Microscope for wafer probers.** The microscope camera (6) is placed above the chamber for visual inspection, **and allows a resolution under 1µ.** The top cover of the vacuum chamber includes a connector for the vacuum tube (7). **The vacuum chamber and actuator are placed on a two-axis UTS150CC, Newport Corporation micropositioning stage with a travel range of 100mm. A block diagram of the proposed system is shown in Figure 3.**

3 Literature review.

The analysis of the resonance frequency can be employed to characterise, and test the functionality of, many types of micro-electro-mechanical systems. It is particularly suitable for devices using capacitive comb drive electrodes (e.g. accelerometers, gyroscopes, mechanical resonators, level sensors, force sensors, and microgrippers), and cantilevers (e.g. force sensors, microgrippers). This method is fast as compared to detailed optical inspection of defects using optical and electron microscopes, and allows the characterisation of the dynamic properties of the microstructures in a non-contact, non-destructive fashion. It is particularly suitable for fragile devices.
To the authors’ knowledge, the proposed method is the first fully automated quality control method for micro- and nano-structures based on the study of the vibration modes at resonance frequency. The idea of relating the vibration modes of resonating microstructures with fabrication parameters developed in the late 1990s. However, the existing literature is concerned only with metrology applications, mainly concerning those quality parameters that are directly related to the vibration modes of the micro-devices.

Early studies focused on the characterisation of physical parameters from the characteristic resonance frequency of the structures. Burns and Helbig [2] estimated the pixel brightness of blurred images of comb drives at different vibration frequencies from a rest image. They used this estimate to generate a set of templates to compare with real microscope camera images of microstructures vibrating at resonance frequency. The frequency of vibration was deduced from the template that best matched the camera image. This method is often referred as the “blur envelope” method [3], and was an improvement upon a more complex procedure based on stroboscopic microcinematography [4]. Stroboscopic illumination was used also by Guo et al. [5] to characterise the dynamic behaviour of micro-electronic structures.

Template matching can be time-consuming when the exact vibration mode of a functional device is not known, since several images and templates must be compared. This is often the case with microstructures, since the vibration mode of each device varies according to the stiffness of the moving parts, and micro-fabrication variables such as the degree of etching. Moreover, in order to be accurate, template matching requires constant experimental conditions (e.g.
illumination), and may not result suitable in a factory environment where the functioning of the test equipment may progressively change with time.

Tanner and his co-workers were the first to use the blur envelope method to infer fabrication parameters of electrostatic comb drives from numerical models of vibrations [3]. They also proposed an alternative technique for determining the resonance frequency of microstructures based on the viscous damping effect of the devices [6].

Other authors investigated the use of laser Doppler vibrometry [7] to measure the resonance frequency of microstructures. Also in this case, analytical vibration models can be used to calculate manually quality parameters (i.e. mechanical properties) and defects of the devices. Lawrence and Rembe [8] employed this method for characterisation of electric comb drives and cantilevers, while Michael et al. [9] used it to inspect membrane structures of micro-electro-mechanical systems.

**Laser Doppler vibrometry has the main drawback that is not an entirely non-intrusive inspection technique.** At the micro-scale, thermal loading may in fact alter the mechanical properties of the devices, or even severely damage the micro-structures [10]. Moreover, the applicability of Laser Doppler vibrometry is also limited by poor spatial resolution, and optical scattering from specular surfaces that may reduce the signal-to-noise ratio in the images [10].

4 Automatic visual inspection algorithms.

The experimental tests were carried out using WMV format files of camera videos showing the vibration of the structures for several seconds. During the period of time monitored in the videos, the frequency of the oscillations was varied continuously from below to above the resonance frequency of the microstructures. The video files
were loaded using M. Richert’s “Mmread” application (available at www.mathworks.nl/matlabcentral/fileexchange), and analysed using the Image Processing Toolbox™ of Matlab (Version 7.4.0.287, R2007a).

Figure 4 shows four video frames taken from a sample video documenting the testing of a defective gripper. In this example, the images were sampled at the rate of two frames per second.

At non-resonance frequency, the amplitude of the vibrations is very small, and both the arms are visible (see Figure 4a). As the period of the oscillations is changed, the shape of both the gripper's arms remains clearly visible until the vibrations approach resonance frequency. Near the frequency of resonance, the vibrations of the non-defective arm become larger and the shape of this element becomes increasingly blurred in the images (see Figure 4b). The defective arm does not resonate, and remain clearly visible in the picture. Figure 4c shows the shape of the two arms at resonance frequency. Figure 4d is taken from the final part of the video, when the frequency of the vibrations has passed the point of resonance and the shape of both the arms becomes visible again.

The experiment described above shows that the functionality of the gripper’s arms can be visually assessed. That is, at resonance frequency the shape of non-defective elements becomes blurred and can be distinguished from the shape of defective arms. The automatic inspection task amounts thus to a machine vision task, where the objective is to detect the amount of blurriness in the picture.

Given the lack of sufficient contrast between the gripper and the background, a simple solution based on the count of edge pixels would not be reliable. A possible solution for the proposed inspection task would be to measure the difference in grey scale
levels from the current frame and the initial crisp picture. At resonance frequency, the
difference would be maximal and large in the case of non-defective parts (both the arms are blurred). This method has the advantage of being conceptually simple, however it turned out to be computationally expensive due to the large number of arithmetic subtractions entailed. For this reason, the above method is not suitable for online processing. Moreover, any slight movement of the gripper during the inspection procedure would likely produce errors. As a consequence, two alternative automatic inspection methods based on QuadTree segmentation [11] and Otsu’s adaptive thresholding [12] algorithm are proposed.

4.1 QuadTree segmentation algorithm.

QuadTrees [13] are recursive data structures that are commonly used to partition two-dimensional spaces into uniform sub-regions. In image processing, they find often application as data compression and image segmentation procedures.

A QuadTree is a tree structure where each node can have up to four children. The segmentation process works as follows. An image is initially split into four regions (quadrants). The regions are usually square or rectangular, but any arbitrary shape can be chosen. Each quadrant is checked against a pre-defined homogeneity criterion. If the criterion is met, the segmentation process is halted. Otherwise, the region is further divided into sub-quadrants and the uniformity test is applied to each of the four partitions. This recursive procedure is repeated for all quadrants, until no further division is possible (i.e. all sub-regions satisfy the uniformity criterion). The pseudocode of the QuadTree algorithm is given in Table 1. Figure 5 shows an example of QuadTree segmentation of a sample binary image representing two
squares. **Figure 5a shows the image segmentation result, figure 5b shows the corresponding QuadTree.**

The proposed algorithm converts the individual colour frames into grey scale images, and uses square blocks for segmentation. The quadrants are checked against similarity of grey scale level. Blocks of non-uniform intensity will be divided until single pixel resolution is achieved. Figure 6 illustrates the result of the segmentation procedure for the four sample images shown in Figure 4.

Once images have been segmented, the number of partitions is counted. Due to the blurred profile of the arms, non-defective device will show a large drop in the count at resonance frequency. A defective device will show a less marked drop if one of the arms is defective, and no drop at all if both the arms are broken. Defective devices can be thus identified from an above-standard minimum count of partitions.

Figure 7 shows the evolution of the quadrant count over the 26 seconds video concerning the test of the device shown in Figures 3 and 5. Two drops in the count can be seen in the plot. The largest drop happens between frames 30 and 49, and corresponds to the resonance frequency of the non-defective arm. A second minor drop can be seen between frames 7 and 27, and probably corresponds to the resonance frequency of the defective arm.

**4.2 Adaptive thresholding binarisation algorithm.**

A very fast alternative method is to binarise the images, and count the number of white pixels. At resonance frequency, the blurred shape of vibrating structures occupies a large portion of the image, and determines a peak in the white pixels count.
Image binarisation is the process of converting a 256 grey-scale image into a two-level black and white image. This is done by fixing a threshold grey level value, and classifying all pixels with intensity values above this threshold as white, and the remaining ones as black. The threshold can be fixed manually by the operator, or set automatically using some heuristic algorithm. The latter case is known as automatic thresholding.

Simple automatic methods include setting the threshold to the mean or median pixel intensity value, or to a valley point of the histogram of the image pixel intensities. These methods assume a clear separation between the object of interest and the background, which is not the case in the presence of blurred objects. Histogram analysis is also computationally quite expensive. A relatively simple and robust adaptive binarisation technique is Otsu’s within-class variance method [12].

Otsu’s method aims at dividing the image into two uniform and clearly separated clusters of pixel intensities. The procedure exhaustively searches the threshold that minimises the within-class variance (clusters uniformity criterion), which is defined as the weighted sum of the pixel intensity variances of the two classes:

\[
\sigma_w(T) = \omega_1(T) \cdot \sigma_1^2(T) + \omega_2(T) \cdot \sigma_2^2(T)
\]  

(1)

where \(T\in[0, 255]\) is the threshold, and \(\omega_i\) and \(\sigma_i^2 (i=\{1, 2\})\) are respectively the number of pixels, and variance of pixel intensity in the two classes. It can be shown that this procedure amounts to maximising the between-class variance (clusters separation criterion)

\[
\sigma_b(T) = \omega_1(T) \cdot \omega_2(T) \cdot \left(\mu_1(T) - \mu_2(T)\right)^2
\]  

(2)

Where \(\mu_i (i=\{1,2\})\) are the mean pixel intensity in the two classes. The pseudocode of Otsu’s adaptive thresholding algorithm is shown in Table 2.
In practice, $\sigma_b^2(T)$ is iteratively calculated for all $T$ values, and the value of $T$ that minimises $\sigma_b^2(T)$ is chosen as the binarisation threshold. At each step, the right-hand side of Equation (2) needs to be only partially recomputed to take into account those pixels that moved from one cluster to the other. Using simple recurrence relations, the between-class variance can be updated efficiently.

After the video frames have been binarised, the number of white pixels in each picture is counted. At resonance frequency, the area occupied in the image by the gripper of a non-defective device will spread due to the blurring. This blurred area will be still brighter than the background, and after binarisation will appear as white. A functional device will thus present a peak in the number of white pixels near resonance frequency.

Figure 8 documents the application of the proposed method. It shows the evolution of the white pixel count after binarisation for the same video of Figure 4. As expected, the plot shows a main increase in the white pixel count between frames 30 and 49, when the non-defective arm resonates, and a second minor increase between frames 7 and 27, when the defective arm resonates.

5 Experimental results.

A first study was carried out on a batch of fifteen videos of vibrating microstructures supplied to Cardiff University by Femtotools GmBH. The batch comprised nine videos of functional, and four of defective microgrippers.

A first experiment was made to measure how much the resonance vibration mode of a component varies between successive stimulations of fixed width. In this test, the
microstructures underwent successive bursts of vibrations at the arms’ resonance frequency. Figures 8a and b show respectively the variation of the QuadTree partitions, and white pixels count over eight successive stimulations. The sampling rate was set to 12 frames per second, and the test lasted 19 seconds. In the first case, the resonance corresponds to a drop in the QuadTree partitions (see Section 4.1), in the second case, it corresponds to an increase in the white pixels count (see Section 4.2).

The first observation that can be made from the two plots is that the QuadTree method produces a much clearer separation between the measures taken at resonance and non-resonance frequency. In both cases, the plots show also that the partitions and white pixels counts are fairly consistent across the eight vibration episodes. Table 3 reports for the gripper of Fig. 8 the average QuadTree partitions and white pixels counts at resonance frequency, their standard deviation, the average QuadTree partitions and white pixels counts at non-resonance frequency, and the difference between the QuadTree partitions and white pixels counts at resonance and outside resonance. In both cases, the difference between the counts at resonance and outside is much larger than the standard deviation of the counts at resonance, and this allows separating clearly the phase of large vibrations from the others.

Experimental observation showed that a possible criterion to identify defective components is the result $\rho$ of the ratio:

$$\rho = \frac{\left| Cr - Cnr \right|}{Cnr}$$

(3)
where $C_r$ is the count of QuadTree partitions (white pixels) at resonance frequency, and $C_{nr}$ is the count of QuadTree partitions (white pixels) at non-resonance frequency. In the case of the QuadTree method, functional components are characterised by a ratio $\rho$ greater than 0.95. That is, when the gripper vibrates at resonance frequency, the QuadTree partition count drops to less than 5% of the initial value at rest. In the case of the adaptive thresholding method, functional components are characterised by a ratio $\rho$ greater than 0.06. That is, when the gripper vibrates at resonance frequency, the white pixel count increases of 6% of its initial value.

It should be stressed that the above values are highly depending on the experimental conditions, and in particular the background, illumination, and image crop. There are also some components that do not vibrate relevantly at resonance frequency, but whose functionality is deemed by the manufacturer still acceptable. These are very infrequent cases which will result in a small fraction of false positives. For this kind of components, manual testing is needed to ascertain whether the functionality is acceptable or not. Two of the samples supplied by the manufacturer for this study belonged to this class and resulted in false positives, the other thirteen grippers were correctly identified.

In terms of processing times, both the algorithms gave acceptable results. Using an Intel Core Duo 2.50GHz processor with 3GB RAM, it took 24.650 seconds to process the 26 seconds video of Figure 4 using the QuadTree segmentation method, and about 8 seconds using Otsu’s method. From the tests performed, given good illumination and background contrast, a sampling rate of one or two frames per second seems adequate to identify defective devices.
The above processing times are only indicative of the real performance of the two algorithms, since the prototype software was not optimised for speed, and it is likely that the use of dedicated hardware may further speed up the performance. The results obtained presently using the prototype software suggest thus that both the algorithms can be implemented in an online application. All the image segmentation (thresholding) procedures can be performed in real time, while the quadrant (pixel) counts can be quickly compared and analysed at the end of the tests.

6 Conclusions and further work

This paper presented a new non-contact, non-destructive procedure for quality control of microgripper arms. The purpose of this study was to prove the possibility of detecting defects in microstructures from their vibration mode at resonance, using standard image processing techniques.

The proposed procedure is based on the analysis of the vibrations of the arms at different frequencies. At their resonance frequency, functional parts show a large peak in the width of the oscillations. A piezoelectric actuator is used to provide the vibration stimulus which is varied over a pre-defined frequency range. A microscope camera is used to take images of the parts as the frequency range is scanned. At resonance, the images of functional components appear blurred due to the large vibrations.

Two image processing techniques were used to measure the degree of blurriness of the pictures, QuadTree segmentation and Otsu’s adaptive thresholding method for image binarisation. These two techniques offer an easy reference since they are well known and effective image processing algorithms. Using the
QuadTree segmentation method, an increase in blurriness in the image can be detected from a drop in the number of partitions. Using Otsu’s method, an increase in blurriness can be detected from an increase in the number of white pixels. In both cases, by fixing a suitable threshold for the number of partitions (white pixels) it is possible to identify defective parts.

Both the procedures gave encouraging results and confirmed the viability of the proposed inspection procedure. As visually shown in the three sample plots of Figures 7, 8, and 9, the QuadTree segmentation method appears to separate more clearly images of functional devices from images of defective ones. In particular, the difference between rest and resonance vibrations is much more evident using the Quadtree algorithm. These results are confirmed by the statistical measurements reported in Table 3.

Due to its superior ability to separate faulty from functional components, the Quadtree algorithm seems at the present the best option for the proposed automatic inspection system. However, it should be stressed that the experimental results presented in this paper refer to a number of videos of vibrating microstructures taken using the first prototype of the proposed system. It is entirely possible that, using future prototypes including improved illumination and background, the results obtained using Otsu’s method might be bettered. Further work should also consider more advanced blur detection techniques such as those proposed by Marziliano et al. [14] and Marichal et al. [15].

At the present, the main strength of Otsu’s method is its relative speed. Compared to the Quadtree segmentation algorithm, Otsu’s method is in fact three times faster. The speed of both algorithms can be improved using
dedicated code optimised for speed. Re-writing the current Matlab routines using a more efficient programming language (e.g. C++) is likely also to shorten the running time of the two algorithms. However, it is worth to notice that even in the present version of the inspection algorithms, the running times are entirely acceptable, and shorter than the time needed to set-up the rig and run the functionality test.

A small percentage of the grippers may not resonate significantly, but still function acceptably. These are however very infrequent cases which will result in a small fraction of false positives. At the present, there are no methods to distinguish these borderline components from defective ones.

The proposed procedure was tested on a set of gripper arms, but it is suitable for inspection of several other fragile micro-electro-mechanical structures such as cantilevers, and electrostatic comb drives. Preliminary tests on the electrostatic comb drives of FemtoTools FT-G100 Microgrippers have given promising results.

The study here presented is meant as a first evaluation and proof of concept of the proposed inspection procedure. Further work is currently done to collect a large and varied sample of defective components in order to carry out a statistical evaluation of the effectiveness of the proposed method, and study the correlation between the vibrational frequency and the QuadTree partitions or white pixel counts.

Acknowledgements

The research described in this paper was supported by the EC FP6 Hydromel project and the EC FP6 Innovative Production Machines and Systems (I*PROMS) Network.
of Excellence. The support of the European Commission is gratefully acknowledged.

Robin Landot worked on the project during his 4 months visit at the MEC.

References


**Word count:**

**Abstract:** 196 words

**Main Body:** 3949 words

**List of Figures:**

- Figure 1: FemtoTools FT-G100 Microgripper.
- Figure 2: The visual inspection system.
- Figure 3: Block diagram of proposed system.
- Figure 4: Pictures of vibrating gripper’s arms.
- Figure 5: Example of proposed QuadTree segmentation procedure.
- Figure 6: Segmentation procedure.
- Figure 7: Defective gripper, evolution of quadrant count.
- Figure 8: Defective gripper, evolution of white pixel count.
- Figure 9: Functional gripper, repeated stimulations.
List of Tables:

Table 1: Quadtree pseudocode.
Table 2: Otsu’s method pseudocode.
Table 3: Functional gripper, repeated stimulations.
Figure 1: FemtoTools FT-G100 Microgripper.

a) gripper.

b) gripper mounted on PCB.
a) inspection rig.  

b) detailed view of inspection rig. 

Figure 2: The visual inspection system.
Figure 3: Block diagram of proposed system.
a) below resonance frequency.  
b) near resonance frequency.  
c) at resonance frequency.  
d) above resonance frequency.

Figure 4: Pictures of vibrating gripper’s arms.
a) segmentation.

b) quadtree.

Figure 5: Example of proposed QuadTree segmentation procedure.
Figure 6: Segmentation procedure.

a) below resonance frequency.  
b) near resonance frequency.

c) at resonance frequency.  
d) above resonance frequency.
Figure 7: Defective gripper, evolution of quadrant count  (26 seconds, 2 frames per second).
Figure 8: Defective gripper, evolution of white pixel count (26 seconds, 2 frames per second).
a) QuadTree partition count

b) White pixels count (Otsu’s method).

Figure 9: Functional gripper, repeated stimulations (19 seconds, 12 frames per second).
Table 1: Quadtree pseudocode.

<table>
<thead>
<tr>
<th>QuadTree Algorithm Pseudocode</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuadTree(I)</td>
</tr>
<tr>
<td>1 I = root</td>
</tr>
<tr>
<td>2 if $\sigma(I) = 0$ /* (uniform pixel intensity) */</td>
</tr>
<tr>
<td>3 return leaf I</td>
</tr>
<tr>
<td>4 else /* $\sigma(I) &gt; 0$, non-uniform pixel intensity */</td>
</tr>
<tr>
<td>5 divide image I in four quadrants</td>
</tr>
<tr>
<td>6 for each quadrant $I_k$</td>
</tr>
<tr>
<td>7 QuadTree($I_k$)</td>
</tr>
</tbody>
</table>

$\sigma(I) =$ standard deviation of pixel gray-scale values of image I
Table 2: Otsu’s method pseudocode.

<table>
<thead>
<tr>
<th>Otsu’s Algorithm Pseudocode</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Compute histogram and pixel counts for each intensity level</td>
</tr>
<tr>
<td>2. Set up initial $\omega_i(T_0)$ and $\mu_i(T_0)$</td>
</tr>
<tr>
<td>3. Step through all possible thresholds $T_k = [0, 255]$</td>
</tr>
<tr>
<td>4. Update $\omega_i(T_k)$ and $\mu_i(T_k)$</td>
</tr>
<tr>
<td>5. $\sigma^2_b(T_k) = \omega_1(T_k) \cdot \omega_2(T_k) \cdot [\mu_1(T_k) - \mu_2(T_k)]^2$</td>
</tr>
<tr>
<td>6. Desired threshold corresponds to the maximum $\sigma^2_b(T_k)$</td>
</tr>
</tbody>
</table>

$\omega_i(T_k) =$ number of pixels belonging to class i  
/* (i = \{black,white\}) */

$\mu_i(T_k) =$ mean pixel intensity in class i

$\sigma^2_b(T_k) =$ inter-class variance
Table 3: Functional gripper, repeated stimulations.

<table>
<thead>
<tr>
<th>Method</th>
<th>Unit</th>
<th>Resonance (ρ)</th>
<th>Std dva (σ)</th>
<th>Rest (r)</th>
<th>Std dva (σ)</th>
<th>ρ-r</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuadTree</td>
<td>Partitions</td>
<td>63</td>
<td>8</td>
<td>4354</td>
<td>182</td>
<td>-4290</td>
</tr>
<tr>
<td>Adaptive Thresh.</td>
<td>White pixels</td>
<td>123507</td>
<td>711</td>
<td>115595</td>
<td>779</td>
<td>7912</td>
</tr>
</tbody>
</table>