Radiometric Measures for Feature Selection In Visual Servoing

M. Ficocelli  F. Janabi-Sharifi

Robotics and Manufacturing Automation Laboratory
Department of Mechanical, Aerospace, and Industrial Engineering
Ryerson University, Toronto, CANADA M5B 2K3
mficocel@acs.ryerson.ca  fsharifi@acs.ryerson.ca

Abstract—The following paper discusses the issue of radiometric constraints for feature selection in the context of visual servoing. Here radiometric constraints are presented and measures are formulated to select the most optimal features in a radiometric sense from the set of candidate features. Experiment results verify the effectiveness of the proposed measures.

I. INTRODUCTION

A typical image of $128 \times 128 \times 8$ provides an overwhelming amount of information for real–time visual servoing. To reduce the amount of data being processed, objects are verified in images by locating a set of features [1]. A feature is any scene property which can be mapped onto the image plane, such as: corner position, edge length, and centroids. Most task objects, with even modest complexity, will contain numerous image features which can be used for tracking. Therefore, if an object has a set of candidate features, $\mathcal{I} = \{f_1, f_2, \ldots, f_N\}$, an optimal subset of features must be selected for visual servoing. Furthermore, as the image changes, the features which are best suited for tracking will also change. For a visual servoing system to be successful, it must have the ability to automatically select features during task operation. Many systems pre–select features for tracking off–line, in an ad–hoc fashion. Unfortunately, this is not a reliable method and leads to task failure [2].

Feature planning is made possible by scoring the candidate features based on the formulated measures and the set of features with the best score is used for each via point of relative trajectory. This method is general enough to be used for both pose–based or image–based visual servoing. Wunsch [4] has addressed the issue of feature selection, but has only based feature selection on occlusion of features and good numerical conditioning, ignoring other system constraints. While these methods ([3], [1], [4]) have all contributed to the problem of feature selection by considering geometrical, control, and image processing issues, they all assume proper lighting.

Prior work has ignored the illumination constraints placed on the system. In a laboratory environment, illumination is set to ideal conditions with a simple black object with white background setup. However, poor lighting has been shown to be a limiting factor and a major concern for the industrial application of visual servoing. The image signal created by the vision sensor is dependent on the illumination of the object and is affected by sensor noise. Under non–ideal conditions, it is difficult to detect and extract meaningful measures. It has been widely known in the sensor planning community that the complexity of image processing can be greatly reduced and made more robust if the lighting of the environment can be set to ideal conditions to properly illuminate certain features [8]. In the field of sensor planning, extensive research has focused on the effects of illumination. Research within sensor planning, uses a generate–and–test approach [5], [6] or a synthesis method [7]. Unfortunately, these methods cannot be directly applied to feature selection. Under feature selection, the system is concerned with the reverse problem. That is, taking the current conditions of the visual servoing system and then determining the most optimal features from the set of candidate features.

This paper will study the radiometric constraints for feature selection in visual servo control applications. The next section will discuss the purpose and function of the feature selection mechanism. Section 3 will describe the radiometric constraints and measures developed in order to score the candidate feature of the task object. The pseudocode for applying the radiometric measures is given. Section 4 will describe the effectiveness of the feature measures through experimentation. Finally, the paper will be concluded in Section 5.

II. OVERVIEW

Similar to [3], we focused on edge based features such as corners and holes, with a score between 0 (poor) and 1 (good). While at first glance, the use of only corners and holes may seem limiting, typical industrial parts have
many such features. Kalman filter, used for pose estimation in position-based visual servoing [3], will require between 3–5 features for tracking. Therefore all possible combinations of features into sets of 3–5 quickly increase into a large set of feature groups to be used for tracking. For example, an object with 18 candidate features results in 8568 possible sets of 5 features.

The goal of this work is to develop feature measures based on the radiometric constraints. These measures serve two purposes:
- To reduce the size of the feature set for analysis; and
- To select the most optimal features.

For objects with a large number of features, it can become computationally intensive to compute the measures for each feature. Reducing the number of features from consideration, early in the selection process, will limit the computational burden. Once the final feature scores have been determined, they should reflect how optimal each feature is for tracking. Optimal features in a radiometric sense are defined here as the features which have as much of the edge points detected as possible, reliable for tracking, and those that provide the most accurate measurements. The radiometric feature measures and procedure proposed here require: a model of the object and if available knowledge of the environment, an illumination model, and a list of candidate features that can be used for tracking. An important aspect of this feature selection mechanism is the formulation of the features, as described in Appendix A.

### III. RADIOMETRIC MEASURES

In order to determine which features should be eliminated from consideration and which features meet the criteria of optimality, the features are evaluated, based on four characteristics:
- Light Visibility, \( LV(f_i, L) \)
- Feature Position, \( FP(f_i, V) \)
- Contrast, \( C(f_i, L, V) \)
- Contrast Sensitivity, \( CS(f_i, L, V) \).

Each feature is evaluated every planning period using four measures derived from the above characteristics. The measures operate on the edges which create the features. For a corner feature, there is a list of \( RE \)'s (Appendix A). Once the measures have been computed for each edge, a measure is computed for each \( RE \). If the \( RE \) fails to meet one of the constraints, it will be removed from further consideration. Once all the \( RE \)'s have been computed for an individual corner feature, the \( RE \) with the best total score will be used for that corner feature. Hole features will be given a single score. Pseudocode for the procedure of feature selection using radiometric measures is given in Table I.

### A. Light Visibility

For an edge to become visible, the edge must be illuminated by a light source. Features which are not illu-

<table>
<thead>
<tr>
<th><strong>Procedure For Optimal Feature Selection</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input</strong></td>
</tr>
<tr>
<td><strong>Output</strong></td>
</tr>
<tr>
<td><strong>Step 1:</strong></td>
</tr>
<tr>
<td><strong>Step 2:</strong></td>
</tr>
<tr>
<td><strong>Step 3:</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Else</strong> **do**</td>
</tr>
</tbody>
</table>
| Take required edge list for \( f_i \) : \( RE = \{ RE_1, \ldots RE_q \} \).
| Set \( k = 1 \), and \( T(f_i) = 0 \).
| For \( \forall RE_k \in RE \) do |
| Set \( \zeta_j = 1 \), \( j = 1 \), \( T(RE_k) = 0 \). |
| **While** \( \zeta_j \neq 0 \) and \( j \leq 4 \) \**do** |
| \( \zeta_j = \text{measure}_j \) |
| \( j = j + 1 \) |
| \( T(RE_k) = T(RE_k) + \zeta_j \) |
| \% measure\(_1\) = \( LV(RE_k, L) \), |
| \% measure\(_2\) = \( FP(RE_k, V) \), |
| \% measure\(_3\) = \( C(RE_k, L, V) \), |
| \% measure\(_4\) = \( CS(RE_k, L, V) \). |
| **If** \( \zeta_k = 0 \) then, discard \( RE_k \) |
| **Else**, add \( T(RE_k) \) to the list of feasible edge list of \( f_i \) |
| **Compute** \( T(f_i) = \max_{RE_k \in RE} T(RE_k) \). |
| **If** \( T(f_i) = 0 \) then, discard \( f_i \) |
| **Else**, add \( f_i \) and \( T(f_i) \) to the list of feasible features. |
| **} **} |
| **Step 4:** | Return features with the highest \( T(f_i) \). |

| **Table I** |
| Pseudocode for feature selection using radiometric constraints. |
minated will be covered under shadow and will not be detectable. Furthermore, if part of the feature is being covered by a shadow, the shadow may be mistaken as part of the feature. Ideally, shadows should be avoided, and the entire feature should be illuminated by the light source with no shadows cast over any part of the feature.

Ray casting can be used to determine if an edge is visible from a light point. This can be done by casting a ray from the light source to \( m \) points along the edge, then checking if any of the rays are blocked by an object. This information can be stored in a light buffer. If the ray reaches the given edge point without intersecting another object then the light buffer \( (M_n) \) is given a value of 1, otherwise if the ray intersects an unknown object a value of 0 will be assigned. In many cases the illumination source is not a point, but rather a linear light source such as a tube. In this case, the light source can be approximated by \( J_l \) point sources.

Therefore, the measure for a corner edge can be devised as:

\[
LV(e_j^k, L) = \frac{1}{m} \sum_{n=1}^{m} M_n, \quad (1)
\]

\[
LV(RE_k, L) = \prod_{e_j^k \in RE_k} LV(e_j^k, L). \quad (2)
\]

In order to evaluate the \( RE_k \), first the individual edge is evaluated using (1), where \( e_j^k \) is the edge \( j \) belonging to \( RE_k \), \( M_n \) is the light buffer value, for the \( n \)th edge point. The \( RE_k \) is then evaluated by multiplying the two individual edge measures (2).

The hole feature measure is similar to the corner feature measure and rays are cast from the light source(s) to the hole edge. The only exception is that each point on the hole must be visible from at least one light source, therefore:

\[
LV(f_i, L) = \begin{cases} 
1 & \text{if } \frac{1}{m} \sum_{n=1}^{m} M_n = 1, \\
0 & \text{otherwise},
\end{cases} \quad (3)
\]

where \( f_i \) is a hole feature of the features set \( \mathcal{F} \).

B. Feature Position

Edges most often occur when two surfaces of the object intersect, or occur between the object boundary and an unknown background. Of the two types of edges, those created by two surfaces intersecting are more reliable than those created between boundary and background. This is because the background may not be known or, unknown objects may be moving in the environment as the object and camera move. For instance, in one sequence the edge against a background may be ideal but in the next sequence the background illumination and/or radiometric properties may change and clash with the edge in question causing ambiguity, making the edge difficult to locate. It is desirable to select edges which are created by known surfaces since radiometric properties are known and illumination is predictable.

This can be computed in a similar manner as the light visibility constraint, using a ray casting technique. A set of \( m \) rays can be cast from the camera focal point towards either side of the edge. In other words, the edge can be approximated by \( m \) points, where a ray will be cast slightly to the right and to the left of the given edge point. Therefore each edge point is composed of 2 rays \( (M^l_n, M^r_n) \). If the ray intersects one of the 2 surfaces which make up the edge, a value of 1 is stored in a ray buffer, otherwise if the ray intersects an unknown background a value of 0 is stored in the ray buffer. The measure for an edge making a corner is given by:

\[
FP(e_j^k, V) = \frac{1}{m} \left( \sum_{n=1}^{m} M_n^l \cdot M_n^r \right), \quad (4)
\]

where \( M_n^l \) and \( M_n^r \) are the ray buffer value for the left and right ray cast to the \( i \)th edge point respectively. The measure for a \( RE \) taking two edges at a time is

\[
FP(RE_k, V) = \prod_{e_j^k \in RE_k} FP(e_j^k, V). \quad (5)
\]

For a hole feature, the entire hole edge should be created by known surfaces of the object and not an unknown background. Therefore,

\[
FP(f_i, V) = \begin{cases} 
1 & \text{if } \frac{1}{m} \left( \sum_{n=1}^{m} M_n^l \cdot M_n^r \right) = 1, \\
0 & \text{otherwise}.
\end{cases} \quad (6)
\]

C. Contrast

Edges occur in an image when there is a large intensity gradient between neighboring pixels. Large is defined by the user and a threshold value is used to determine whether or not an edge point is present at a given image point. For an edge to be recognized in an image, the contrast across the edge must surpass the threshold value. The use of more edge points will provide more accurate feature measurement. Therefore, it is desirable to detect as many of the edge points as possible to achieve the most accurate measurements.

Again, using ray casting from the light source(s) and camera, and a lighting model, an illumination intensity value can be computed on either side of the given edge. A contrast value across the edge can be computed by subtracting the two illumination values \( C_n = |DN_n^l - DN_n^r| \), where \( DN_n^l \) and \( DN_n^r \) are the pixel illumination value to the left and right of the \( n \)th edge point respectively. Using the contrast value \( C_n \), a contrast measure can be expressed as:

\[
C(e_j^k, L, V) = \frac{1}{m} \sum_{n=1}^{m} c_n, \quad (7)
\]

where \( c_n \) represents the \( n \)th edge point, and

\[
c_n = \begin{cases} 
1 & \text{if } C_n > T_{\text{thres}}, \\
0 & \text{otherwise}.
\end{cases} \quad (8)
\]
Therefore, \( RE \) of a corner is scored as
\[
C(RE_k, L, V) = \prod_{e^k_j \in RE_k} C(e^k_j, L, V).
\] (9)
The score for a hole feature is given by
\[
C(f_i, L, V) = \begin{cases} 
1 & \text{if } \frac{1}{m} \sum_{n=1}^{m} c_n = 1, \\
0 & \text{otherwise},
\end{cases}
\] (10)

D. Contrast Sensitivity

Often when detecting edges in an image, the contrast across the entire edge will not surpass the threshold value by a large margin. The sensitivity of an edge near the threshold value will affect the accuracy of feature measurements. Edge points with contrast values near the threshold may easily pass to the other side of the threshold because of noise and small variations in object pose and illumination. Noise present in images could be falsely detected as edge points. Also, an edge point contrast value that is near the threshold crossing can be undetected because of sensor noise effects. This then causes the accuracy of the measured feature point. It has been shown in [5] that the variance of an edge point \( \sigma^2 \) is inversely related to contrast \( C^2 \) and proportional to the noise variance in the image \( \sigma^2 = \kappa \frac{C^2}{\sigma^2} \).

Edges with contrast values near the threshold are also susceptible to changes in object pose, and illumination. A small change in illumination or object pose can change the contrast across the edge enough to make a large portion of the edge undetectable. Therefore, edges, with contrast values further from the threshold are more robust to changes, can be used for a longer sequence of images, and provide more accurate measurements. It is desirable then to select features which have contrast values which are not sensitive to the threshold value.

The contrast sensitivity constraint is a measure of how the contrast varies along the edge with respect to the threshold. This can be measured as
\[
CS(e^k_j, L, V) = \frac{1 - e^{-B_{CS} M_{CS}^k}}{(1 - e^{-B_{CS}})},
\] (11)
where \( DN_{\text{max}} \) is the maximum digital number produced by the sensor. \( M_{CS}^k \) is an average measure of how close the contrast of the given edge, \( e^k_j \) is near the threshold value \( T_{\text{thres}} \), i.e.,
\[
M_{CS}^k = \frac{1}{nT} \sum_{n=1}^{nT} |C_n - T_{\text{thres}}|,
\] (12)
where \( nT \) is the number of contrast values that are above the threshold value, and \( C_i \) is the edge point contrast value above the threshold. \( B_{CS} \) is a sensitivity constant that effects the speed at which the measure approaches 1. The selection of \( B_{CS} \) is dependent on a noise model of the sensor and fluctuations of the illumination source. For example, if the sensor is ideal with little or no noise then \( B_{CS} \) should be large and reach saturation quickly. This is because if the contrast is in the vicinity of the threshold, this would be sufficient for safe edge detection without missing edge points. Large differences between contrast values and the threshold do not lead to great improvements in the detectability and robustness of the edge points being detected. For a sensor which produces noisy data, \( B_{CS} \) should be selected small enough such that the given measure will reach 1 slower. This is because the contrast values further from the threshold will have more weight than those values near the threshold.

The measure for the \( RE_k \) of a corner is
\[
CS(RE_k, L, V) = \prod_{e^k_j \in RE_k} CS(e^k_j, L, V).
\] (13)
For a hole, the sensitivity measure is
\[
CS(f_i, L, V) = \frac{1 - e^{-B_{CS} M_{CS}^k}}{(1 - e^{-B_{CS}})}.
\] (14)

IV. EXPERIMENTAL RESULTS

Experimental data was collected to verify the accuracy of the proposed measures and the correlation between feature scores and accuracy of feature extraction. The corner measures were tested using an object accurately placed on a matte surface within the working volume of a coordinate measuring machine (CMM) (Figure 1). Two incandescent light sources were used to illuminate the object, each were approximated as point sources. Images of the block were taken under different illumination conditions, and with the camera moved to different positions. A total of 30 images were taken. Examples of different images of the block are given in Figure 2. A required edge list, Table II, was produced for the corners of the object.

An example of the score values for image D of Figure 2 is given in Table II. The image was processed, and
the corner points were extracted. The extracted corner value was compared to the expected corner value, this is shown in Table II. The expected corner value was determined using a camera model, and the known object position within the CMM. As it can be seen, features that would be selected for tracking based on the radiometric scores are: $f_3, f_4, f_5, f_7, f_8$. These features are also among the most accurately extracted. Furthermore, the radiometric measures were able to select the best RE for each feature. For example, for feature $f_3$, $RE_3$ should be used to extract corner $f_3$ as $RE_3$ provides the most accurate corner location (Table II). This is reflected in the feature scores as $RE_3$ is the highest rated of the three $RE$’s. This testing method was repeated for all 30 images of the block.

The procedure described above was also used to test the radiometric measures for an object with hole features. Once radiometric measures and error values were computed for all hole and corner features, a correlation coefficient was determined to reveal a relationship between feature error value and feature score. A correlation coefficient of -0.74 was computed for the radiometric measures versus the computed error. This shows that there is a strong relationship between the radiometric feature score and feature extraction error, where a high radiometric score is associated with accurate feature extraction.

V. CONCLUSION

Feature selection is an important aspect of any visual servoing system. The features used for tracking cannot remain the same throughout the tracking phase of visual servoing. Instead, the system should have the ability to switch features which provide the most accurate and reliable information. While this issue has been considered by others, they have ignored the effects of lighting. However, lighting is an important contributor to the quality of pose estimation.

Four radiometric measures have been proposed here to grade/score each feature based on current conditions of the visual servoing system. As it was shown, there is a strong correlation between total radiometric score and feature extraction error. These measures can be combined with those developed in [3] to produce a complete list of task measures for feature selection.

Appendix A: FEATURE SET

A task object with $n$ features, form the set of candidate features $\mathcal{F} = \{f_1, f_2, \ldots, f_n\}$, where $f_i$ is the $i$th feature of the list of features. A hole feature is defined by an edge forming a closed boundary. A corner feature is defined as the intersection of at least two edges. Often there will be $k$ edges intersecting at a corner. The corner can then be defined by any two of the edges. Therefore, there will be $q = \binom{k}{2}$ possible combinations of edges to define the given corner feature, $f_i$. The total list of edge combinations to represent a corner feature is referred to as a required edge list ($RE$), where $RE = (RE_1, RE_2, \ldots, RE_q)$ is the entire set of required edge list for the candidate corner feature, with $RE_k = (e_j^k, e_l^k)$. Here $e_j^k$ is the edge $j$ associated with the $k$th required edge list.

Acknowledgment

This research was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) through research grant #203060 – 98.

References

<table>
<thead>
<tr>
<th>Feat. No.</th>
<th>Required Edge List</th>
<th>Total</th>
<th>Error (pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$RE_1(1, 4), RE_2(1, 9), RE_3(4, 9)$</td>
<td>(---)</td>
<td>(---)</td>
</tr>
<tr>
<td>2</td>
<td>$RE_1(1, 2), RE_2(2, 10), RE_3(1, 10)$</td>
<td>(- 1.92 -)</td>
<td>(- 0.558 -)</td>
</tr>
<tr>
<td>3</td>
<td>$RE_1(2, 11), RE_2(2, 3), RE_3(3, 11)$</td>
<td>(2.17 2.68 3.06)</td>
<td>(1.0719 1.54 0.61)</td>
</tr>
<tr>
<td>4</td>
<td>$RE_1(4, 3), RE_2(4, 12), RE_3(3, 12)$</td>
<td>(- - 3.92)</td>
<td>(- - 0.567)</td>
</tr>
<tr>
<td>5</td>
<td>$RE_1(10, 5), RE_2(5, 6), RE_3(10, 6)$</td>
<td>(2.37 2.46 1.75)</td>
<td>(0.626 - -)</td>
</tr>
<tr>
<td>6</td>
<td>$RE_1(6, 11), RE_2(6, 7), RE_3(11, 7)$</td>
<td>(2.27 2.38 3.05)</td>
<td>(- - 0.701)</td>
</tr>
<tr>
<td>7</td>
<td>$RE_1(12, 7), RE_2(7, 8), RE_3(12, 8)$</td>
<td>(3.9 3.71 3.8)</td>
<td>(0.437 0.511 0.573)</td>
</tr>
<tr>
<td>8</td>
<td>$RE_1(5, 8), RE_2(5, 9), RE_3(8, 9)$</td>
<td>(3.78 - -)</td>
<td>(0.664 - -)</td>
</tr>
</tbody>
</table>