METHOD OF INCLINATION MEASUREMENT FOR MULTI-SENSOR OBJECT RECOGNITION

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ABSTRACT. Aimed at the object recognition problem with multiple characteristic indices, a new fusion method for multi-sensor data is proposed based on inclination measurement. The method applies the entropy weight to reflect the function of each characteristic index in information fusion, calculates the inclination between the object type and ideal solution, and uses the relative closeness degree to give the rule of recognition. The example of part recognition proves that the method is both feasible and effective.

Keywords: multi-sensor, data fusion, object recognition, entropy weight, closeness degree

1. Introduction. In intelligence system, multiple sensors are usually used to acquire information and proceed to object recognition. Many different fusion methods for multi-sensor object recognition have been developed [1-11], for example, methods based on Shafer-Dempster evidence theory [1-3], methods based on fuzzy theory [4-6], Bayesian approach [7], variable fuzzy method [8], extension method [9], Dual Hierarchical Models [10], and multiplex complex amplitude [11], etc. Papers [8] and [9] investigated multi-sensor object recognition problem with multiple characteristic indices, but the weights of the characteristic indices for object types in both papers were given artificially, which is too absolutely and empirically. In fact, the different characteristic indices play different roles in the process of information fusion.

To overcome this drawback, avoid the subjective randomness of selecting weights of the characteristic indices, and improve the trustworthy and scientific degree of the object recognition result, this paper defines the entropy weights of characteristic indices, and proposes a new method based on inclination measurement for multi-sensor object recognition. The key features of the results obtained in this paper compared with existing ones exist in three points. First, the work transforms dexterously the characteristic matrix of object recognition system into the characteristic membership degree matrix. Secondly, the entropy weights reflect objectively the function for different characteristic indices during the process of information fusion. Finally, the method of inclination measurement can enlarge the range of the support degree between object types, therefore greatly improve the trustworthy degree of the object recognition.

2. System of Multi-sensor Object Recognition. Suppose that the object database involves n object types s_1, ..., s_n, each object type has m characteristic indices. Let x_{ij} denote the characteristic value for object type s_j with respect to the i - th characteristic index. So, we have the characteristic matrix for the recognition system

\[ X = (x_{ij})_{m \times n} \] (1)
Now, we utilize many different sensors to measure the every characteristic index of some unknown object. Assume that \( X_i \) is the measured value for the \( i - \text{th} \) characteristic of the unknown object, \( i = 1, \ldots, m \). Then, the task of data fusion is to discriminate the type ascription of the unknown object according to the measurement results \( X_1, \ldots, X_m \).

3. **Inclination Measurement Method.** First, applied the max-min membership function, the characteristic matrix \( X \) is transformed into the characteristic membership degree matrix \( R = (r_{ij})_{m \times n} \), where

\[
r_{ij} = \min\{X_i, x_{ij}\}/\max\{X_i, x_{ij}\}
\]

\( r_{ij} \) represents the relative distance between the measurement and characteristic value.

3.1. **Entropy weight.** The word "entropy" comes from Greece. Shannon termed information entropy as the uncertainty of the signal coming from the information source. A gain in entropy means the loss of information. The better ordered a system, lesser the entropy. Since the object database contains multiple different characteristic indices. Every index acts as a different role in data fusion. If the characteristic values of all object types with respect to one index are same, this index has no influence on the object recognition. The greater is the deviation between the characteristic values of different object types with respect to same one index, the stronger is the influence of these characteristic values on object recognition, and the bigger are their entropy weights.

**Definition 3.1.** Given the characteristic membership degree matrix \( R \), the entropy of \( i - \text{th} \) characteristic is defined by [12]

\[
H_i = -k \sum_{j=1}^{n} f_{ij} \ln(f_{ij})
\]

where \( f_{ij} = r_{ij}/\sum_{j=1}^{n} r_{ij} \). If \( r_{ij} = 0 \), then assume \( f_{ij} \ln(f_{ij}) = 0 \).

**Definition 3.2.** Define the entropy weight for the \( i - \text{th} \) characteristic as

\[
w_i = (1 - H_i)/(m - \sum_{i=1}^{m} H_i)
\]

Let \( W = (w_1, \ldots, w_m) \) be the vector of entropy weight. It is easy to know from definitions 1 and 2 that the entropy weight comes from the information of the object database itself. It can objectively and really embody the function of each characteristic index in data fusion.

3.2. **Inclination measurement.** The weighted membership degree matrix can be calculated as follows

\[
Z = (z_{ij})_{m \times n}
\]

where \( z_{ij} = w_i r_{ij} \). According to the weighted membership degree matrix, the object type \( s_j \) can be expressed as \( s_j = (z_{ij}, \ldots, z_{mj}) \). Since the task of object recognition is to select the object type which is the closest to the measurement of all sensors, this paper applies the inclination measurement to recognize object according to the theory of multi-object decision making [12]. We first give the following pertinent definitions.

**Definition 3.3.** Define the positive ideal solution (PIS) by \( s^+ = (z^+_1, \ldots, z^+_m) \), the negative ideal solution (NIS) by \( s^- = (z^-_1, \ldots, z^-_m) \), where

\[
z^+_i = \min_j z_{ij}, z^-_i = \max_j z_{ij}, i = 1, \ldots, m
\]

Then, we obtain the inclination between the object type \( s_j \), PIS and NIS [12], respectively

\[
\theta(s_j, s^+) = \arccos(s_j s^+/(\|s_j\| \|s^+\|))
\]

\[
\theta(s_j, s^-) = \arccos(s_j s^-/(\|s_j\| \|s^-\|))
\]
Definition 3.4. Define the relative closeness degree of the object type $s_j$ with respect to PIS $s^+$ as
\[ C_j = \frac{\theta(s_j, s^-)}{\theta(s_j, s^-) + \theta(s_j, s^+)} , \quad j = 1,\cdots, n \] 

(9)

Obviously, the value of $C_j$ lies between 0 and 1. If $s_j = s^+$, then $\theta(s_j, s^+)=0, C_j = 1$; if $s_j = s^-$, then $\theta(s_j, s^-)=0, C_j = 0$. The larger the relative closeness degree $C_j$ is, the closer the $j$-th object type to PIS $s^+$, the farther the $j$-th object type from NIS $s^-$, the better the corresponding object type.

3.3. Rule of object recognition. On the basis of the above discussion, the rule of object recognition is: if
\[ C_k = \max_j \{C_j\} \] 

(10)

then the unknown object is the type $s_k$.

4. Simulation Example. To illustrate the above algorithm in detail, we apply the algorithm to the multiple parts recognition example in [8]. In order to realize the parts automatic recognition and classification of intelligent robot, assume there are four part types $s_1,\cdots,s_4$ and four characteristic indices. Let $\theta_1,\cdots,\theta_4$ represent the four characteristic indices, respectively. Table 1 describes the characteristic value.

<table>
<thead>
<tr>
<th></th>
<th>$\theta_1$</th>
<th>$\theta_2$</th>
<th>$\theta_3$</th>
<th>$\theta_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_1$</td>
<td>1.30</td>
<td>1.86</td>
<td>3.07</td>
<td>2.75</td>
</tr>
<tr>
<td>$s_2$</td>
<td>2.43</td>
<td>3.71</td>
<td>2.28</td>
<td>2.34</td>
</tr>
<tr>
<td>$s_3$</td>
<td>2.18</td>
<td>1.93</td>
<td>1.37</td>
<td>1.52</td>
</tr>
<tr>
<td>$s_4$</td>
<td>1.85</td>
<td>2.52</td>
<td>2.97</td>
<td>1.93</td>
</tr>
</tbody>
</table>

We input the signals of sensors into the computer through data acquisition. After information separation and data fusion on characteristic-level, the four characteristic indices of some unknown object and the measurement data are reported in Table 2.

<table>
<thead>
<tr>
<th></th>
<th>$\theta_1$</th>
<th>$\theta_2$</th>
<th>$\theta_3$</th>
<th>$\theta_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_i$</td>
<td>2.15</td>
<td>2.30</td>
<td>2.80</td>
<td>2.12</td>
</tr>
</tbody>
</table>

Table 2. Characteristic observations for unknown part

From (1) and (2), we get the characteristic matrix and membership degree matrix, respectively
\[ X = \begin{pmatrix} 1.3 & 2.43 & 2.18 & 1.85 \\ 1.86 & 3.71 & 1.93 & 2.52 \\ 3.07 & 2.28 & 1.37 & 2.97 \\ 2.75 & 2.34 & 1.52 & 1.93 \end{pmatrix} \] \[ R = \begin{pmatrix} 0.6047 & 0.8848 & 0.9862 & 0.8605 \\ 0.8087 & 0.6199 & 0.8391 & 0.9127 \\ 0.9121 & 0.8143 & 0.4893 & 0.9428 \\ 0.7709 & 0.9060 & 0.7170 & 0.9104 \end{pmatrix} \]

The entropy and entropy weight are calculated by (3) and (4) as follows
\[ H = (H_1,\cdots,H_4) = (0.9892, 0.9931, 0.9681, 0.9962), \]
\[ W = (w_1,\cdots,w_4) = (0.2020, 0.1292, 0.5974, 0.0712). \]

The weighted membership degree matrix is obtained from (5)
\[ Z = \begin{pmatrix} 0.1221 & 0.1143 & 0.5892 & 0.0613 \\ 0.1634 & 0.0801 & 0.5013 & 0.0650 \\ 0.1842 & 0.1052 & 0.2923 & 0.0671 \\ 0.1557 & 0.1171 & 0.4283 & 0.0648 \end{pmatrix}. \]
From (6), we have PIS and NIS, respectively
\[ s^+ = (0.0613, 0.0650, 0.0671, 0.0648), \]
\[ s^- = (0.5892, 0.5013, 0.2923, 0.4283). \]

According to (7)-(9), the computation results for the inclination and the relative closeness degree are presented in Table 3.

<table>
<thead>
<tr>
<th></th>
<th>( s_1 )</th>
<th>( s_2 )</th>
<th>( s_3 )</th>
<th>( s_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inclination to PIS</td>
<td>0.1096</td>
<td>0.1522</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Inclination to NIS</td>
<td>0.3689</td>
<td>0.2780</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Closeness degree</td>
<td>0.7710</td>
<td>0.6462</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

It can be seen from Table 3 that \( C_4 = 1 \) is the maximum. Thus, by (10), the unknown part belongs to part type 4. This is accordance with the result of [8]. If we view the relative closeness degree of this paper as the support degree, then though the recognition results by the variable fuzzy method [8] and this paper’s method are same, the distinguishing degrees of object recognition from both methods are greatly different. Table 4 presents the compared results. The range is referring to the difference of the support degree between type 4 and other types.

<table>
<thead>
<tr>
<th></th>
<th>( s_1 )</th>
<th>( s_2 )</th>
<th>( s_3 )</th>
<th>( s_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>This paper</td>
<td>0.7710</td>
<td>0.6462</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Range</td>
<td>0.2290</td>
<td>0.3538</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Paper[8]</td>
<td>0.366</td>
<td>0.581</td>
<td>0.556</td>
<td>0.79</td>
</tr>
<tr>
<td>Range</td>
<td>0.424</td>
<td>0.209</td>
<td>0.234</td>
<td></td>
</tr>
</tbody>
</table>

Table 4 shows that the ranges of parts 2 and 3 by this paper are 0.3538 and 1, respectively, more than the corresponding ranges 0.209 and 0.234 by [8]. Simultaneously, the sum of range by this paper is 1.5828, which is greatly bigger than the range sum by [8] 0.867. Obviously, the more the range, the higher the distinguishing degree of recognition is. Furthermore, compared with [8], this paper’s method greatly reduces the computational complexity. The above discussion indicates the method of this paper is superior to the variable fuzzy method to some extent.

5. **Conclusion.** From a new angle of multi-object decision making, a novel fusion method based on inclination measurement is proposed for multi-sensor object recognition in this paper. The core of this method is to use the entropy weight to depict the function of the characteristic indices. The entropy weight objectively reflects the importance of each characteristic index in information fusion. It can perfectly avoid the subjective randomness of selecting index weight and improve the trustworthy and scientific degree of the recognition result. The method is easy to be operated and implemented on a computer.

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