Object Detection, Classification, & Tracking Technologies

Vol. 4554

PROCEEDINGS OF SPIE
SPIE—The International Society for Optical Engineering

Object Detection, Classification, and Tracking Technologies

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Chairs/Editors

22–24 October 2001
Wuhan, China

Sponsored by
SPIE—The International Society for Optical Engineering
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Supported by
National Natural Science Foundation of China
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Published by
SPIE—The International Society for Optical Engineering

SPIE PROCEEDINGS SERIES

Volume 4554

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Please use the following format to cite material from this book:

Author(s), "Title of paper," in *Object Detection, Classification, and Tracking Technologies*, Jun Shen, Sharatchandra Pankanti, Runsheng Wang, Editors, Proceedings of SPIE Vol. 4554, page numbers (2001).

ISSN 0277-786X
ISBN 0-8194-4282-8

Published by
SPIE—The International Society for Optical Engineering
P.O. Box 10, Bellingham, Washington 98227-0010 USA
Telephone 1 360/676-3290 (Pacific Time) • Fax 1 360/647-1445
http://www.spie.org/

Printed in the United States of America.

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FootPrints: An IR Approach to Human Detection and Tracking

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ABSTRACT

Web retailers use cookies to find out where there customers went in their sites, regardless of whether they'bought anything there, so that their web site designers can make the site more attractive and present more closely targeted information to the customer. The result is more happy customers, fewer dissatisfied ones (notoriously hard to measure in any other way) and an increase in their conversion rate, the percentage of visitors who buy something. Conversion rate is one of the most talked-about statistical parameters in the retail trade. Web retailers know their conversion rate, but for bricks-and-mortar shops, it is usually very poorly known - it is far from unusual for a retail executive to overestimate the conversion rate by a factor of two or three.

Footprints System provides information for studying the movement of people in indoor spaces, particularly shoppers in retail environments. It is designed to provide detailed information on the movements of customers in stores, providing bricks-and-mortar stores the same sorts of information about their customers as web stores have: knowing where people walked and stopped, combined with what they bought (obtained from point-of-sale data), will allow the retailer rapid feedback on staffing, store layout, merchandising, price points, the effectiveness of in-store advertising and signage, and accurate estimation of sales loss due to shortages. It does this while strictly preserving each individual's privacy.

Footprints is an online diagnostic system for retail stores, designed to provide detailed information on the movements of customers in stores, while strictly preserving each individual's privacy. The key to satisfying these seemingly contradictory requirements is to work in the thermal infrared, like a porch light sensor, and at very low spatial resolution, so low as to suppress all individual characteristics.

Footprints System uses many small, inexpensive, semi-autonomous sensors mounted in the ceiling of the retail space. These sensors detect heat radiation from warm bodies just as automatic porch light sensors do. Like a porch light sensor, Footprints sees people as warm blobs, and measures only the positions of these objects, not their identities or even their species. The resolution is sufficiently coarse (one pixel per floor tile, 60 cm per pixel line pair) that essentially no information about the person's identity, sex, age, or ethnicity can be extracted from it. (People all look alike in the thermal infrared, particularly when the pixel size is bigger than their heads.) Variations in signal strength have more to do with clothing and hair style than with physical size, and skin color has no effect on the data whatsoever. This is a vitally important property for customer acceptance and for IBM's reputation for respecting and protecting people's privacy.

Footprints uses many small, cheap, semi-autonomous sensors mounted in or on the ceiling of the retail space. Each sensor has 96 pixels, arranged as an 8 × 12 rectangular array, and typically takes data at a rate of 5 Hz per pixel, time-synchronized accurately. The optical system is merely a moulded polyethylene Fresnel lens of 60 mm diameter, whose focal length is chosen to provide a 30 cm pixel pitch when mounted at ceiling height. The sensors typically mount through a ceiling tile like an intercom speaker, on an approximately 3 metre grid, but no alignment is necessary, as the trajectory extraction layer configures that automatically. Each sensor communicates with the base station via a 900 MHz frequency- hopping spread spectrum RF network, arranged in a star topology and based on scheduled broadcast and reporting times for each sensor, which allows the sensors to turn off their RF sections almost all the time. This adds to the complexity of the network design, but saves a lot of power: Footprints sensors require less than 100 mW in full operation with the RF off, and so can be powered by distributed low voltage dc, a wall brick, primary battery, or solar cells and a NiCd battery. The RF section runs at a duty cycle of much less than 1coverage) without blowing the power budget. The very low resolution also means that we can cover a huge area with very few pixels, leading to low cost per square foot ($1to3$) and that the communications and processing requirements even for very large spaces (100,000 square feet for a large store) are similarly modestone PC and a total raw data rate of 1MB/s. The data are stored as T values for each pixel in each sensor, as a function of time, for the trajectory extraction layer to process. Here we describe the layered approach to design of the Footprints system which consists of the following processing layers: image acquisition, preprocessing, tracking, and application layer. We will also present preliminary results of the system.

Contents

SESSION 6 CLASSIFICATION TECHNOLOGIES III

POSTER SESSION

Invited Paper

An object recognition approach based on feature fusion

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ABSTRACT

Multi-sensor information fusion plays an important pole in object recognition and many other application fields. Fusion performance is tightly depended on the fusion level selected and the approach used. Feature level fusion is a potential and difficult fusion level though there might be mainly three fusion levels. Two schemes are developed for key issues of feature level fusion in this paper. In feature selecting, a normal method developed is to analyze the mutual relationship among the features that can be used, and to be applied to order features. In object recognition, a multi-level recognition scheme is developed, whose procedure can be controlled and updated by analyzing the decision result obtained in order to achieve a final reliable result. The new approach is applied to recognize work-piece objects with twelve classes in optical images and open-country objects with four classes based on infrared image sequence and MMW radar. Experimental results are satisfied.

Keywords: information fusion, feature quality, feature ordering, feature selecting, object recognition

1. INTRODUCTION

Multi-sensor information fusion plays an important pole in object recognition and many other application fields since it can integrate characteristics apperceived of different sensors and advance recognition or decision performance. Fusion performance is tightly depended on the fusion level selected and the approach used. There are three main fusion levels, that is, data level, decision level and feature level. Data level fusion is to integrate the multi-sensor data, which is the closest to the original signal and adapted to the multi-sensor with same data types, and widely applied to remote sensing fields. Decision level fusion is to integrate the local decisions from multi-sensor used and is widely utilized in many fields, though information of multi-sensor data is not utilized sufficiently. Feature level fusion is to integrate the features from multi-sensor, and is more suitable to multi-sensor with different data types. It can utilize the information more fully from all sensors used and generate some new features indeed. It is a potential and difficult fusion level. There are less methods and systems for feature level fusion in recurrent references.

There are two key issues in feature level fusion. One is extracting and selecting suitable features from the used multi-sensor data, which are powerful for making decision. The other is using efficient integrated method in order to obtain best decision performance for the requirement given. In this paper, a scheme of extracting and selecting suitable features and a multi-level object recognition scheme are developed for a classification demand given. The scheme of extracting and selecting suitable features consists of two parts: one is to collect possible features extracted by general mathematical and physical methods, the other is to analyze the mutual relationship among the features that can be used, and to order and select features. The multi-level procedure of object recognition can be controlled and updated by analyzing the decision result in order to get a final reliable result. The new approach is applied to recognize work-piece objects with 12 classes in optical images and open-country objects with 4 classes based on infrared image sequence and MMW radar. Experimental results

Object Detection, Classification, and Tracking Technologies, Jun Shen, Sharatchandra Pankanti, Runsheng Wang, Editors, Proceedings of SPIE Vol. 4554 (2001) © 2001 SPIE · 0277-786X/01/$15.00

are satisfied.

This paper is organized as following. A scheme of extracting and selecting features is presented in Section 2. A multi-level decision scheme of object recognition is discussed in Section 3. The experiment is shown and discussed in Section 4.

2. A SCHEME OF EXTRACTING AND SELECTING FEATURES

There are a plenty of characteristics for each object class. These characteristics could be apperceived by various sensors and transformed into feature format by mathematical or information processing approaches. Features are, in general, the concise parameter descriptions of object characteristics. For a given recognition application, there might be some powerful and key features for classification decision. Question is how to find a normal scheme for extracting and selecting them. A significant technical way is first to set up a feature base, which collects possible algorithms for extracting object features, then to develop a normal method for evaluating decision performance of features in order to select optimal features. We present a concept of feature decision quality, and develop a computation method for evaluating decision performance of the features.

2.1 Quality parameters of a feature

A perfect feature of an object class should be distinguishable, concentrated and stable so that it can offer the most powerful contribution to an application. In order to evaluate performance of each feature two quality parameters are defined, respectively.

Representation quality of a feature of an object class is a kind of measurement of its description ability to this object class, which is associated with concentration and stability of the feature attribute distribution. Let there are C object categories $\{c_\alpha, \alpha = 1, \cdots, C\}$ and M features $\{f_i, i = 1, \cdots, M\}$ for each object class, in which distribution of each feature for each class is supposed as a normal format.

Definition 1 The quality parameters $RS_{\alpha i}$ and $RD_{\alpha i}$ of a feature f_i for representing an object class α are defined as following,

$$RS_{\alpha i} = \frac{\sigma_{\alpha i}}{\mu_{\alpha i}}, \qquad RD_{\alpha i} = |u_{\alpha i} - l_{\alpha i}| \tag{1}$$

where $u_{\alpha i}$ and $l_{\alpha i}$ are feature values, where the feature distribution value are equal to some less fixed value, for an example, 0.01 maximum.

Decision quality of a feature of an object class is a kind of measurement of decision ability to recognize the object class. As we know, a feature is actually served for multi-class. Less decision quality appears if there are overlapped distributions of different classes in a feature axis. The decision quality of a feature is tightly dependent on the decision demand that involves the specified features joined and the entity classes to be judged.

For the ith feature, each object class has a relative distribution and an interval along the feature axis. For the α th class, all other classes whose distributions overlap with its distribution along the ith axis can be found. whose number and class indexes are denoted as $N_{\alpha i}$ and $\{n_{\alpha i}\}$.

Definition 2 If there are some distributions overlapped of different object classes in a feature f_i, the decision certainty degree $QC_{\alpha i}$ and decision uncertainty degree $DQ_{\alpha i}(\beta)$ of the feature f_i for assigning an object class α are defined as following:

$$QC_{\alpha i}=\frac{1}{RD_{\alpha i}}\int_{l_{\alpha i}}^{u_{\alpha i}}\frac{g_a(x)}{g_{\alpha i}(x)}dx,\quad DQ_{\alpha i}(\beta)=\frac{1}{RD_{\alpha i}}\int_{l_{\alpha i}}^{u_{\alpha i}}\frac{g_{\beta\alpha i}(x)}{g_{\alpha i}(x)}dx \qquad \beta\in\{n_{\alpha i}\} \tag{2}$$

where $g_{\alpha i}(x)$ is the distribution of α class in f_i, and other is computation values

$$g_{\beta\alpha i}(x)=\begin{cases} g_{\beta i}(x) & g_{\alpha i}(x)\geq g_{\beta i}(x),\ \ l_{\alpha i}<x<u_{\alpha i} \\ 0 & other \end{cases}$$

$$g_a(x)=\begin{cases} g_{\alpha i}(x) & g_{\beta\alpha i}(x)=0 \\ \underset{\gamma}{Max}\, f_{\gamma\alpha i}(x) & g_{\gamma\alpha i}(x)\neq 0,\gamma\in\{n_{\alpha i}\} \end{cases}$$

2.2 Quality parameters of a pair of features

Decision quality of a pair of features involves mainly the contribution relation between the pair in making decision, which is either mutual complementary or mutual correlative. The contribution relation can be estimated in identifying some object class by analyzing whether they have same uncertainty in identifying the object classes. It is obvious that the relation of the pair of features changes while either object classes or class number varies. In order to measure the mutual relation between a pair of features, two quality parameters are defined.

Definition 3 A pair of features, f_i and f_j, should have some mutual complementary characteristic each other for assigning the object class α if they satisfy the condition $\{n_{\alpha i}\}\cap\{n_{\alpha j}\}=\phi$, and the decision certainty degree of the pair of features can be computed using the following formula,

$$QC_{\alpha-ij}=\begin{cases} QC_{\alpha i}\times QC_{\alpha j} & \{n_{\alpha i}\}\cap\{n_{\alpha j}\}=\varphi \\ 0 & other \end{cases} \tag{3}$$

Definition 4 A pair of features, f_i and f_j, should have some mutual correlative characteristic each other for assigning the object class α if they satisfy the condition $\{n_{\alpha i}\}\cap\{n_{\alpha j}\}\neq\phi$, and the decision certainty degree of the pair of features can be computed using the following formula,

$$DQ_{\alpha-ij}=\begin{cases}\sum_{\beta}\left[DQ_{\alpha i}(\beta)\times DQ_{\alpha j}(\beta)\right] & \beta\in\{n_{\alpha i}\}\cap\{n_{\alpha j}\}\\ 0 & other\end{cases} \quad (4)$$

For general multi-decision cases, each pair of features is often mutual complementary for identifying some object class but correlative for identifying other object classes simultaneously. The specified mutual relation characteristics of each pair of features in a multi-class decision case are tightly associated with a special decision demand that involves entity object categories, class number and their attribute distributions in the features. A method for representing these mutual relationships is developed..

Definition 5 Given a decision demand, decision certainty degree QC_{ij} and decision uncertainty degree DQ_{ij} of each pair of features, f_i and f_j, used in the entity decision can be described as following:

$$QC_{ij}=\sum_{\alpha}QC_{\alpha-ij}\ , \qquad DQ_{ij}=\sum_{\alpha}DQ_{\alpha-ij} \quad (5)$$

where $i,\ j=1,\cdots,M,\ i\neq j,\alpha=1,\cdots,C$.

2.3 Feature ordering

For multi-class decision with multi-feature, there are different technical ways to investigate decision quality of a feature set. It is necessary to determine some criteria and relative measure for evaluating and ordering features. In this paper, a belief criterion is developed based on decision parameters of a pair of features. In order to estimate decision performance of each pair of features for the whole decision demand, their decision certainty degree for some object classes and decision uncertainty degree for other object classes should be considered simultaneously. Now index-order matrix is first defined, and basic decision belief of a feature is followed presented.

Definition 6 Given a decision demand, index-ordering matrix U of a feature set used can be represented as following

$$U=\left\lfloor\frac{QC_{ij}}{1+DQ_{ij}}\right\rfloor \quad i,j=1,\cdots,M,\ j\neq j,j<i \quad (6)$$

Definition 7 Given a decision demand, basic decision belief (BDB) of a feature, for a given decision demand can be described by following

$$BDB_i=\sum_{j}u_{ij} \quad i,j=1,\cdots,M,\ i\neq j,\ j<i \quad (7)$$

All feature of a feature set could be ordered based on equation (7) for the decision demand given. Power features will occupy the front locations.

3. AN OBJECT RECOGNITON SCHEME

We think that an advanced object recognition system should have the following characteristics. (1) It can determine the key or powerful features adaptively for a given recognition task. (2) It can achieve an optimal decision performance with fewer features. (3) A feedback decision procedure can be utilizes by analyzing the result obtained in order to get a final reliable result. For feature level fusion, items to be fused are features that are from the sensors used. In this paper, an object recognition scheme is presented, and shown in Figure 1.

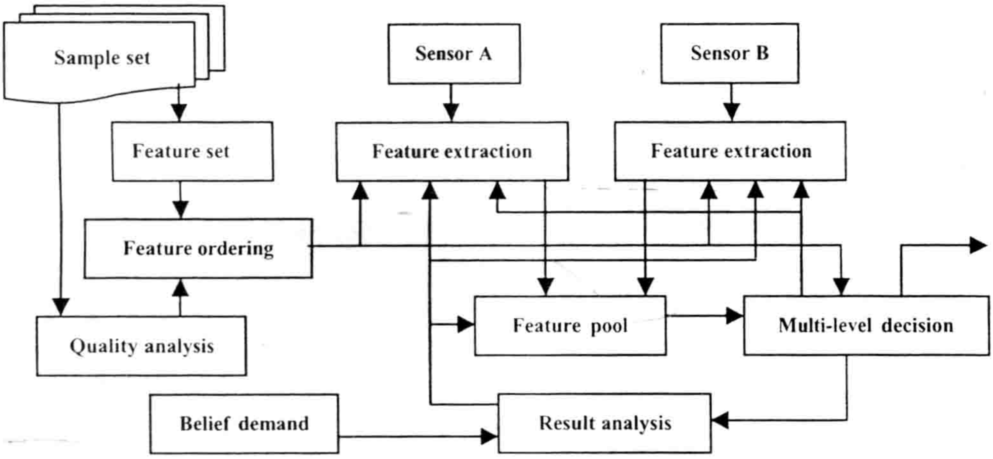

Figure 1. An object recognition scheme

The object recognition scheme consists of three parts. The first part is to order features that can be used based on given sample set and feature extraction methods. The second part is to extract the features from the input data according to the guide of the training result for sample data set, and put them into a feature pool, which collects the features that would be used in thereafter decision processing. The third part is to make a classification decision that might be multi-level processing. A decision process of object classification is guided by the feature order. First two or three features with high order are firstly used with a cumulating fashion, and the obtained results are followed judged if it is correct according to the identification criteria. The feature with the next highest order is then added for making decision if above result is not accepted, and new results are examined with same way until the decision belief expected is achieved. The identification criteria consist three items. (1) The class assignments of the input object obtained by the feature accumulation fashion should be consistent. (2) The belief values of correct recognition should be gradually increased while number of features accumulated is augmented. (3) All or most features could be used if the class assignment is not among the categories to be recognized. In this scheme, decision is mainly based on multi-feature, and some typical fusion methods such as D-S evidence theory can be utilized.

4. EXPERIMENTS

The new approach is applied to recognize work-piece objects with 12 classes in optical images and open-country objects with 4 classes based on infrared image sequences and MMW radar.

In work-piece object recognition, an object base with 100 classes in Figure 2 is used, which is originally from reference [3] and then formed by us. Each object class of the object base has 10 kinds of features, and 10 image samples, whose size is 128x128 with various variations in location, rotation and scale. Index of object class is from 0 to 99. Four object groups with 12 different classes are selected for the experiment, and are denoted as A, B, C and D, respectively.

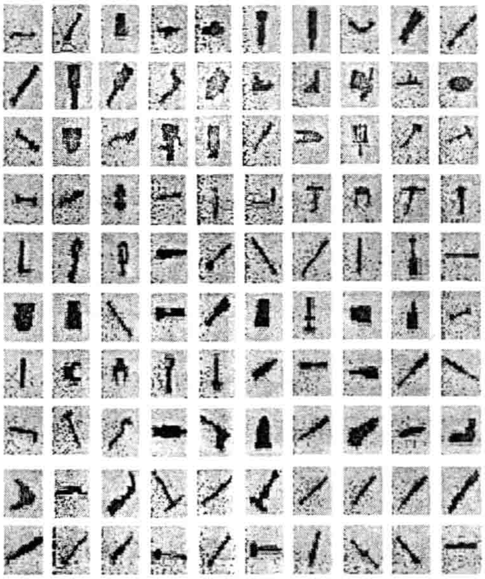

Figure 2. 100 object classes

Table 1 Feature order of the work-piece groups

Group	Index	Feature order
A	12—23	F9、F6、F3、F7、F1、F2、F4、F0、F5、F8
B	37—48	F9、F2、F1、F7、F4、F3、F6、F5、F0、F8
C	62—73	F2、F1、F7、F4、F3、F6、F5、F0、F9、F8
D	87—98	F1、F3、F2、F9、F4、F7、F6、F0、F5、F8

Table 2 Classification probabilities

Probability	First one	First two	First three	First four	First five
Correct	81.40	92.25	96.12	98.26	99.42
Error	18.60	7.75	3.82	1.74	0.58

Table 3 Classification results

	Samples in the class aspects				Samples out of the class aspects				
Group	First one	First two	First three	First four	First two	First three	First four	First five	First eight
A	104	16			1	4	1	2	1
B	110	10			4	3	1	1	
C	104	6	6	4		3	4	1	1
D	102	18			1	4	1	2	1

We can see that the orders of feature decision performance are changed while classification demands vary in Table 1. The classification experiment is parted into two aspects according to the input patterns types that are belong to the categories to be recognized or not. It shows that more than 96% probability of correct classification is achieved with first three features in our experiment, and the approach developed is potential.

In MMW/FLIR object recognition, an object base with 4 classes is used, which is obtained from open country. MMW radar and FLIR imagery instrument are coaxial. Four features are extracted from the power spectrum of the radar data received. The FLIR image size is o 352x288, and another four features are extracted from the image sequence apperceived. The object classes include man by bicycle, running man, car and truck.

Table 4 shows four object groups and the feature orders in each class group. It indicates feature decision performances are varied in different decision demands.