社団法人　情報処理学会　研究報告
IPSJ SIG Technical Report

2003－ＩＣＳ－133 (24)
2003／9／15

Peculiarity Oriented Analysis in Multi-People Tracking Images

Muneaki OHSHIMA†, Ning ZHONG††, Y.Y. YAO†††, and Shinichi MURATA††††

† Maebashi Inst. of Tech.　460–1 Kamisadori–cho, Maebashi 371–0816, Japan
†† Dept. of Infor. Eng., Maebashi Inst. of Tech.　460–1 Kamisadori–cho, Maebashi 371–0816, Japan
††† Univ. of Regina　Regina, Saskatchewan S4S 0A2, Canada
†††† Oki Electric Industry Co., Ltd.　1–16–8, Chuoh–Cho, Warabi–City 335–0004, Japan

Abstract　In the place in which many people gather, we may find a suspicious person who is different from others from a security viewpoint. In other words, the person who takes a peculiar action is suspicious. In this paper, we describe an application of our peculiarity oriented mining approach for analysing in image sequences of tracking multiple walking people. A measure of peculiarity, which is called *peculiarity factor*, is investigated theoretically. The usefulness of our approach is verified by experimental results.

Key words　Peculiarity Oriented Mining, Analysis of Multi-People Tracking Images

特異性指向マイニングによる複数人物追跡画像の解析

大島　宗哲†　　鍾　　寧††　　Y.Y.　Yao†††　　村田　伸一††††

† 前橋工科大学　〒 371–0816 群馬県前橋市上佐鳥町 460–1
†† 前橋工科大学 情報工学科　〒 371–0816 群馬県前橋市上佐鳥町 460–1
††† Univ. of Regina　Regina, Saskatchewan S4S 0A2, Canada
†††† 沖電気工業株式会社　〒 335–0004 埼玉県蕨市中央 1–16–8
E-mail: †ohshima@wi-lab.com, ††zhong@maebashi-it.ac.jp, †††yyao@cs.uregina.ca,
††††murata533@oki.com

あらまし　安全の為に, 多くの人が集まるような場所では不審人物を発見することが重要である. 言い換えると, この不審人物とは他の人たちとは異なった行動をしている人と言える. 本論文では, 複数の人物が映った動画から人物追跡技術によって得られた人物追跡画像に対し, 特異性指向データマイニングを適用する. また, データの特異性を表す *Peculiarity Factor* について理論的に考察し, 実験結果からこの手法の有用性を示した.

キーワード　特異性指向マイニング, 複数人物追跡画像の解析

1. Introduction

In the place such as a station or an airport in which many people gather, many sacrifices will come out when the acts of terror happen. From a security viewpoint, we need to find a suspicious person in such a place. Although the suspicious person can be discovered by using the surveillance camera with a video, not all people can be checked automatically.

We observed that a suspicious person usually takes action which is different from other people, so-called *peculiar action*, such as coming from and going to the same place and stopping at some place. Hence, our peculiarity oriented mining approach [6], [7] can be used to analyse such data automatically.

In this paper, we describe an application of our peculiarity oriented mining approach for analysing in image sequences of tracking multiple walking people. Section 2. investigates how to identify peculiar data in our peculiarity oriented mining approach. Section 3. discusses the application of our approach for automatically analysing image sequences of tracking multiple walking people, which were obtained by using the surveillance camera. The experimental results show the usefulness of our approach. Finally, Section 4. gives concluding remarks.

2. Peculiar Data Identification

The main task of peculiarity oriented mining is the identification of peculiar data. An attribute-oriented method, which

Table 1 A sample table (relation)

A_1	A_2	$\dots$	A_j	$\dots$	A_m
x_{11}	x_{12}	$\dots$	x_{1j}	$\dots$	x_{1m}
x_{21}	x_{22}	$\dots$	x_{2j}	$\dots$	x_{2m}
$\vdots$	$\vdots$		$\vdots$		$\vdots$
x_{i1}	x_{i2}	$\dots$	x_{ij}	$\dots$	x_{im}
$\vdots$	$\vdots$		$\vdots$		$\vdots$
x_{n1}	x_{n2}	$\dots$	x_{nj}	$\dots$	x_{nm}

analyzes data from a new view and is different from traditional statistical methods, is recently proposed by Zhong *et al.* [6], [7].

2.1 A Measure of Peculiarity

Peculiar data are a subset of objects in the database and are characterized by two features:

(1) very different from other objects in a dataset, and

(2) consisting of a relatively low number of objects.

The first property is related to the notion of distance or dissimilarity of objects. Institutively speaking, an object is different from other objects if it is far away from other objects based on certain distance functions. Its attribute values must be different from the values of other objects. One can define distance between objects based on the distance between their values. The second property is related to the notion of support. Peculiar data must have a low support.

At attribute level, the identification of peculiar data can be done by finding attribute values having properties (1) and (2). Table 1 shows a relation with attributes $A_1, A_2, \dots, A_m$. Let x_{ij} be the value of A_j of the i-th tuple, and n the number of tuples. Zhong *et al.* [6], [7] suggested that the peculiarity of x_{ij} can be evaluated by a *Peculiarity Factor*, $PF(x_{ij})$,

$$PF(x_{ij}) = \sum_{k=1}^{n} N(x_{ij}, x_{kj})^{\alpha}, \tag{1}$$

where N denotes the conceptual distance, α is a parameter to denote the importance of the distance between x_{ij} and x_{kj}, which can be adjusted by a user, and $\alpha = 0.5$ as default.

With the introduction of conceptual distance, Eq. (1) provides a more flexible method to calculate peculiarity of an attribute value. It can handle both continuous and symbolic attributes based on a unified semantic interpretation. Background knowledge represented by binary neighborhoods can be used to evaluate the peculiarity if such background knowledge is provided by a user. If X is a continuous attribute and no background knowledge is available, we use the following distance:

$$N(x_{ij}, x_{kj}) = |x_{ij} - x_{kj}|. \tag{2}$$

If X is a symbolic attribute and the background knowledge for representing the conceptual distances between x_{ij} and x_{kj} is provided by a user, the peculiarity factor is calculated by the conceptual distances [2], [4], [6], [7]. The conceptual distances are assigned to 1 if no background knowledge is available.

Table 2 Attribute values and its frequency

attribute value	frequency
x_1	n_1
x_2	n_2
$\vdots$	$\vdots$
x_h	n_h
Total	n

Based on peculiarity factor, the selection of peculiar data is simply carried out by using a threshold value. More specifically, an attribute value is peculiar if its peculiarity factor is above minimum peculiarity p, namely, $PF(x_{ij}) \geqq p$. The threshold value p may be computed by the distribution of PF as follows:

$$p = mean\ of\ PF(x_{ij}) + \beta \times standard\ deviation\ of\ PF(x_{ij}) \tag{3}$$

where β can be adjusted by a user, and $\beta = 1$ is used as default. The threshold indicates that a data is a peculiar one if its PF value is much larger than the mean of the PF set. In other words, if $PF(x_{ij})$ is over the threshold value, x_{ij} is a peculiar data. By adjusting the parameter β, a user can control and adjust threshold value.

2.2 Analysis of the Peculiarity Factor

A question arises naturally is whether the proposed peculiarity factor reflects our intuitive understanding of peculiarity (i.e. the properties (1) and (2) as mentioned previously). More specifically, whether a high value of Eq. (1) indicates x_{ij} occurs in relatively low number of objects and is very different from other data x_{kj}. Although many experiment results have shown the effectiveness of the peculiarity factor, a detailed analysis may bring us more insights [5].

In order to analyze Eq. (1), we adopt a distribution form of attribute value. In Table 2, let $\{x_1, \dots, x_h\}$ be the set of distinguishing values of an attribute. With respect to the distribution, the $PF(x_i)$ can be easily computed by:

$$PF(x_i) = \sum_{k=1}^{h} n_k \times N(x_i, x_k)^{\alpha} \tag{4}$$

Let now consider two special cases, in order to have a better understanding of PF.

Case 1-1. Assume that all attribute values have the same frequency, namely, $n_1 = n_2 = \dots = n_h = h/n$. In this case, we have:

$$PF(x_i) = \frac{h}{n} \sum_{k=1}^{h} N(x_i, x_k)^{\alpha}. \tag{5}$$

Since h/n is a constant independent of any particular value, the PF value depends only on the total distances of x_i and other values. A value far away from other values would be considered to be peculiar.

Case 1-2. Assume that the distance between a pair of distinguish values are the same, namely, $N(x_i, x_k) = C$ for $i \neq k$ and $N(x_i, x_i) = 0$. In this case, we have:

$$PF(x_i) = (n - n_i)C = nC - n_i C. \tag{6}$$

Since nC is a constant independent of any particular value, the PF value is monotonic decreasing with respect to the value of n_i. A value with low frequency will have a large PF, and in turn, is considered to be peculiar. As expected, the distances between x_i and other values are irrelevant [5].

In general, PF depends on both the distribution n_k and the individual distances $N(x_i, x_k)$. Several qualitative properties can be said about the peculiarity factor based on Eq. (4):

- A value with low frequency tends to have a higher peculiarity value. This follows from the fact $\sum_{k=1}^{k=h} n_k = n$ and there are $n - n_i$ distances to be added for x_i.
- Each term in Eq. (4) is a product of frequency n_k and the distance $N(x_i, x_k)$. This suggests that a value far way from more frequent values is likely to be peculiar. On the other hand, a value for away from less frequent values may not necessarily peculiar, due to a small value of n_k. A value closer to very frequent values may also be considered to be peculiar, due to the large value of n_k. Those latter properties are not desirable properties.
- Eq. (4) can be rewritten as:

$$PF(x_i) = n \sum_{k=1}^{h} \frac{n_k}{n} \times N(x_i, x_k)^\alpha. \tag{7}$$

Thus, the peculiarity factor is in fact a weighted average of distances between x_i and other values. It is the expected distance of $N(x_i, x_k)^\alpha$ with respect to probability distribution $(n_1/n, n_2/n, \ldots, n_h/n)$. Under this view, a value is deemed peculiar if it has a large expected distance to other values.

From the above analysis, we can conclude that the peculiarity factor has some desired properties and some undesired properties. The main problem may stem from the fact that average is used in the calculation of peculiarity factor. A best average does not necessarily imply a best choice. Consider the following distribution:

attribute value	frequency
$x_1 = 1$	$n_1 = 10$
$x_2 = 5$	$n_2 = 1$
$x_3 = 10$	$n_3 = 10$
Total	$n = 21$

Assume $\alpha = 1$ and $N(x_i, x_k) = |x_i - x_k|$. We have the following peculiarity values:

$$PF(x_1) = 64, \quad PF(x_2) = 60, \quad PF(x_3) = 62.$$

On the other hand, $x_2 = 5$ seems to be peculiar rather the other two. Furthermore, although a user can adjust the parameter β in the selection of threshold value for peculiarity data selection, its usefulness is limited. The notion of peculiarity, as defined by Eq. (4), mixes together two notions of frequency and distance. Although it is based on a sound theoretic argument, its meaning cannot be simply explained to a non-expert.

Furthermore, α in Eq. (1) can be also considered two special cases with respect to the two cases stated above.

Case 2-1. Assume $\alpha >> n$. This means $N(x_{ij}, x_{kj})^\alpha >> n_i$. Hence,

$$PF(x_i) = \sum_{k=1}^{h} n_k \times N(x_i, x_k)^\alpha \simeq \sum_{k=1}^{h} N(x_i, x_k)^\alpha. \tag{8}$$

This case is the same as Case 1-1 stated above. In other words, the PF value depends only on the total distances of x_i and other values.

Case 2-2. Assume $\alpha \to 0$. Hence,

$$N(x_{ij}, x_{kj}) = \begin{cases} 1 & (x_{ij} \neq x_{kj}) \\ 0 & (x_{ij} = x_{kj}) \end{cases} \tag{9}$$

This case is the same as Case 1-2 stated above, when $C = 1$. Based on Eq. (6), we have

$$PF(x_i) = (n - n_i)C = nC - n_i C = n - n_i. \tag{10}$$

In other words, the PF value depends only on the distribution n_k.

Figure 1 shows the relationship between the distance and PF when α changed in Eq. (1). By adjusting the parameter α, a user can control and adjust the degree of PF that depends on both the distribution and the distance. And according to experience, $\alpha = 0.5$ will get a good balance between the distribution and the distance.

2.3 An Algorithm

Based on the above-stated preparation, an algorithm of finding peculiar data can be outlined as follows:

Step 1. Execute attribute oriented clustering for each attribute, respectively.

Step 2. Calculate the peculiarity factor $PF(x_{ij})$ in Eq. (1) for all values in an attribute.

Step 3. Calculate the threshold value in Eq. (3) based on the peculiarity factor obtained in *Step 2.*

Step 4. Select the data that are over the threshold value as the peculiar data.

Step 5. If the current peculiarity level is enough, then goto *Step 7.*

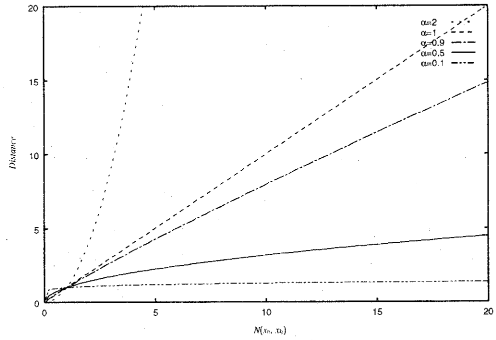

Figure 1 The relationship between the distance and PF when α changed

Step 6. Remove the peculiar data from the attribute and thus, we get a new dataset. Then go back to *Step 2.*

Step 7. Change the granularity of the peculiar data by using background knowledge on information granularity if the background knowledge is available.

Furthermore, the algorithm can be done in a parallel-distributed mode for multiple attributes, relations and databases because this is an attribute-oriented finding method.

3. Application in Analysing Image Sequences of Tracking Multiple Walking People

Peculiarity oriented mining has been applied to analyse image sequences of tracking multiple walking people. The path of tracking data of each walking people are used to discover the person action pattern and to detect a person's unique action. The data were obtained by using the surveillance camera with a video, and preprocessed by using person tracking technology developed at OKI Electric Industry Co., Ltd. In this experiment, we used the video photoed at a station ticket wicket (Figure 2). The purpose is to discover the person who has taken a suspicious action.

3.1 Data Preparation

The original attributes on tracked image sequences of multiple walking people might not be suitable directly for our peculiarity oriented mining approach. Hence, a key issue is how to generate the attributes to meet our needs from the original data.

At first, the raw data are changed into the coordinates and are given in CSV format for every frame by person tracking technology. Each instance is indicated in the following attributes.

- ID: The unique ID attached to each people under tracking.
- FrameNumber: The frame number in the video.

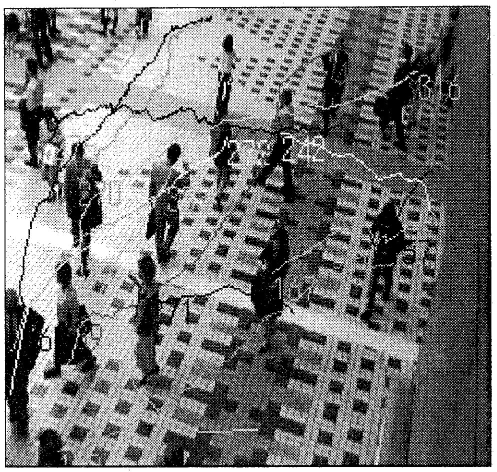

Figure 2 multiple walking people at a station ticket wicket

- Status: The following states are used to describe the state of tracking.

0: Undefined (unstable state at the time of a tracking start),

1: Definited (stable tracking), and

2: Lost (out of the tracking).

- X_1 (coordinate): Raw data under tracking – a left end is 0 and a right end is 256.
- Y_1 (coordinate): Raw data under tracking – a up end is 0 and a down end is 240.
- X_2 (coordinate): The smoothed data – a left end is 0 and a right end is 256.
- Y_2 (coordinate): The smoothed data – a up end is 0 and a down end is 240.

In this experiment, we do not use attributes *Status*, X_1 and Y_1, although *Status* is used in person tracking technology. Further, X_2 and Y_2 will be regarded as the same cases as referred to X_1 and Y_1, respectively. This is because X_1 and Y_1 are unstable, and they are covered by X_2 and Y_2.

The following attributes are used as an attribute for specifying a person's action; *ID, In* (the direction included in the photography range), *Out* (the direction left from the photography range), and *seg-n* (the segment number: the number changed the advance direction after going into the photography range before coming out of the range). *In* and *Out* are calculated from the coordinates, respectively, when a person appears for the first time, and the last. *seg-n* is calculated from the number of the divided line segment.

3.2 Linearization of Walking Data

Usually, people goes straight on to the destination from the current position when acting with a goal, if no obstacle prevented him/her from going. In other words, he/she will walk back and forth in a certain range, not to mention a de-

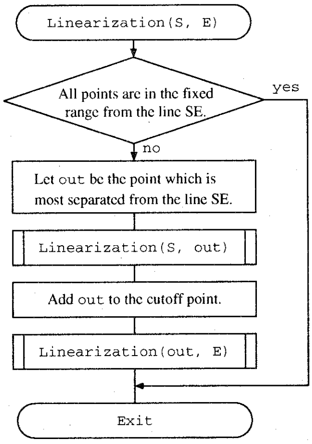

Figure 3 Linearization flowchart

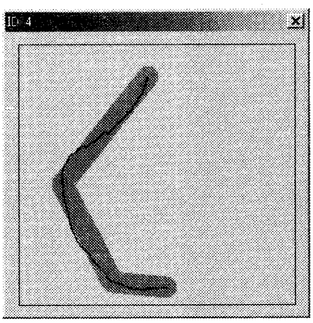

Figure 4 An example of the linearization

tour, or will stop, if the person is at a unusual state, without a specific goal, and so on. Hence, whether the behavior of a person is usual or not can be analysed by calculating the segment number (i.e. the number of changed direction) in the linearized walking data of each person.

In order to calculate the segment number, linearization of walking data needs to be first performed. An algorithm of linearization can be outlined in Figure 3. An example of the linearization is shown in Figure 4.

3.3 Simulations

3.3.1 Experiment 1

The following parameters were used to calculate PF, $\alpha = 0.5$, $\beta = 1$. And the linearization of walking data has a 20-point error margin. There are 26 persons who have been judged as taking peculiar actions in this experiment. A part of the result is given Table 3.

By comparing the result shown in Table 3 with the actual movie, we can see that only 3 persons can be regarded as peculiar ones. The reason why the result is not more exact is that the attributes used in this experiment may be insufficient. Hence, it is necessary to add attributes for describing human's action pattern more specifically.

Table 3 A part of result 1

ID	In	Out	seg-n
2004	down	up	3
2010	up	left	2
2019	rightup	leftup	1
2039	rightup	leftdown	2
2175	down	leftdown	2
2270	up	left	1
2272	leftdown	up	2
2353	leftdown	center	1

3.3.2 Experiment 2

Based on the above experiment, we added a new attribute, *frame-n* (i.e. number of frames), which was staying at the photography range. And the parameters for calculating PF were set to $\alpha = 0.5$, $\beta = 2$. The reason why we set $\beta = 2$ is that points which persons pass in different photography ranges have a bigger unevenness. For example, some people passes along middle and other persons passe along an end of the photography range.

The result of this experiment is shown in Table 4. We can see there are 5 persons judged as taking peculiar action in this experiment. However, the value of attributes *In* or *Out*, "center", means the person who was in the photography range at the time of the start of photography, or the end. Hence, such person cannot be judged to take a peculiar action. As a result, only 3 persons have been considered as taking peculiar actions.

Table 4 Result 2

ID	In	Out	seg-n	frame-n
2004	down	up	3	286
3020	left	up	3	286
4004	center	up	2	286
5024	right	up	2	279
5171	down	center	2	275

3.3.3 Experiment 3

Based on experiments 1 and 2, we added two more attributes *speed* (pixel/frame-n) and *angle* (the average angle of all turnings, i.e., the total angle/# of turnings) for experiment 3. The angle can be calculated by the linearized segment. It was set to 180 degree if not turning. Furthermore, the parameters for calculating PF were set to $\alpha = 0.5$, $\beta = 1$ for attribute *speed*, and to $\alpha = 0.5$, $\beta = 2$ for attribute *angle*, respectively.

As a result as shown in Table 5, we can see there are 16 persons, including the case as shown in Figure 4, who have been judged as taking peculiar actions.

Although no all the detected persons are peculiar ones, all suspicious persons have been discovered. We observed that the pattern of the whole person's stream will change depending on different time zones. Hence, it is necessary to compare

Table 5 A part of result 3

ID	In	Out	seg-n	frame-n	speed	angle
2004	down	up	3	286	1.0	119
2010	middle	left	2	105	1.7	128
3020	left	leftup	2	286	1.0	136
3031	up	leftdown	3	237	1.1	120
5134	down	rightup	3	223	1.2	134

the detected peculiar actions with a more general pattern in each time zone.

4. Conclusions

We presented an application of our peculiarity oriented mining approach for analysing in image sequences of tracking multiple walking people. The strength and usefulness of our approach have been investigated theoretically and demonstrated by experimental results.

In order to increase accuracy, it is necessary to evaluate in multiple stages. Moreover, a general rule (i.e. the pattern of the whole person's stream) needs to be discovered, and will be helpful to recognize suspicious persons quickly.

Another further work is to compare our work with the computer vision literature, and perform more thorough evaluation of our approach.

Refetences

[1] Hilderman, R.J. and Hamilton, H.J. (2001) "Evaluation of Interestingness Measures for Ranking Discovered Knowledge", D. Cheung, G.J. Williams, Q. Li (Eds) *Advances in Knowledge Discovery and Data Mining*, LNAI 2035, Springer, 247-259.

[2] Lin, T.Y. (1998) "Granular Computing on Binary Relations 1: Data Mining and Neighborhood Systems", L. Polkowski and A. Skowron (eds.) *Rough Sets in Knowledge Discovery*, Vol. 1, Physica-Verlag, 107-121.

[3] Suzuki E. (1997) "Autonomous Discovery of Reliable Exception Rules", *Proc Third Inter. Conf. on Knowledge Discovery and Data Mining (KDD-97)*, AAAI Press, 259-262.

[4] Yao, Y.Y. (1999) "Granular Computing using Neighborhood Systems", Roy, R., Furuhashi, T., Chawdhry, P.K. (eds.) *Advances in Soft Computing: Engineering Design and Manufacturing*, Springer, 539-553.

[5] Yao, Y.Y. and Zhong, N. (2002) "An Analysis of Peculiarity Factor in Peculiarity Oriented Data Mining", T.Y. Lin and Setsuo Ohsuga (eds.) *Proc. ICDM workshop on Foundation of Data Mining and Knowledge Discovery (FDM02)*, 185-188.

[6] Zhong, N., Yao, Y.Y., and Ohsuga, S. (1999) "Peculiarity Oriented Multi-Database Mining", J. Zytkow and J. Rauch (eds.) *Principles of Data Mining and Knowledge Discovery*, LNAI 1704, Springer, 136-146.

[7] Zhong, N., Ohshima, M., and Ohsuga, S. (2001) "Peculiarity Oriented Mining and Its Application for Knowledge Discovery in Amino-acid Data", D. Cheung, G.J. Williams, Q. Li (eds.) *Advances in Knowledge Discovery and Data Mining*, LNAI 2035, Springer, 260-269.

[8] Zhong, N., Yao, Y.Y., Ohshima, M., and Ohsuga, S. (2001) "Interestingness, Peculiarity, and Multi-Database Mining", Proc. 2001 IEEE International Conference on Data Mining (IEEE ICDM'01), IEEE Computer Society Press, 566-573.