Detecting Abnormal Behaviors of Small Flying Robots for Automatic Trajectory Control

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***Abstract*—Change points are abrupt variations in a data sequence. Detection of change points is useful in modeling, analyzing, and predicting time series in application areas such as robotics and teleoperation. In this paper, a change point is defined to be an abrupt variation in one of its derivatives. This paper presents a reliable method for detecting abrupt variations within three dimensional trajectories of UAV robots. The problem of determining one or more abnormal flight behavior is considered in regular and irregular trajectory data from teleoperation. We examine the geometric detection algorithm and illustrate the use of the method on real data examples.**

***Index Terms*—change point, abnormal behavior, trajectory, teleoperation, abrupt variation**

I. Introduction

Tele-operators of UAV robots go through with many teleoperation trainings in three dimensional virtual environments to perform space teleoperation tasks, for example, deployment of UAVs, satellites, maintenance of payloads and constructions, inspection and repair of the bridges, and construction of space station. Robotic operators generally use two hand controllers for translation and rotation of the UAVs via bare eye or installed cameras. In addition, the robotic workstation consists of video displays and control panels. The visual feedback on UAV's movement and clearance to the surrounding structures are provided by cameras, which are positioned around the airframe and mounted on the gimbal link [1].

The robotic system in UAVs has multiple control modes, e.g., reference axis rotation, change of point of monitor views, etc., which can happen during performing specific tasks, but this adds cognitive complexity and mental weakness, and confusion even [2]. Robotic operators' errors regarding mode awareness can lead to the arm movement in unanticipated and possibly dangerous directions. Even operators rely on a limited number of 2-dimensional monitors to perform 3-dimensional space tasks. This spatial difference could give rise to mode awareness errors when different information is provided from another camera which has different point of view, e.g., rotated angle or different reference of frame [1]-[4].

This situation is frequently encountered in teleoperation when the coordinate systems for motor control and visual feedback are misaligned. Suitable sensors and telemetry from the remote system can provide data to correct the users' control coordinates so that all displayed motion is parallel to the users' physical input motion. However, it is often the case that this signal processing is not possible. Correction of rotated control frames is also problematic since users may be required to visualize motion in multiple rotated input frames simultaneously [4].

A final issue associated with rotated control frame corrections arises due to the correction essentially being a type of partial automation. Since such automation can fail, users need practice to work without it. The failure of the infrastructure correcting rotated controls frames is analogous to failure of a telerobot resolved control system, which could necessitate that the operator fall back to a joint angle control technique [4], [5].

Accordingly, both for training and task definition, the cause of users' task difficulties associated with operation during control frame rotation needs to be understood [6]. Though the telerobot control misalignment problem occasionally has been studied with respect to the users' pitch, roll, and yaw control coordinates, most previous studies have been of yaw angle misalignment. Moreover, there have been no comparative studies of large ranges of misalignment in all three canonical misalignment axes [5], [6].

The consequences of any significant collision resulting from incorrect control could threaten both mission success and even human safety. Therefore, operators must have the cognitive abilities to correctly interpret the information which is required to perform proper control [7].

Detection of change points is a process to identify abrupt changes in the sequential data (i.e. time series, signal, trajectory or tracking data).

The detection of change points (hereafter, discontinuities) in derivatives is important in a broad range of applications. In particular, determining derivative discontinuities within three dimensional trajectories provides a rich source of information about the key physical attributes that can be used for human behavior analysis, feature extraction or difficulty estimation. Knowledge of the discontinuities can be used to analyze the data and describe the phenomena appropriately. Hence it is necessary to locate and determine all of the discontinuities in any time series data.

Methods capable of detecting discontinuities have been proposed in [8]-[11]. However, those approaches can only

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approximate functions in two dimensional and work well if their models have a certain level of smoothness and regularity. The detection of discontinuities and estimate their locations are challenging in three dimensional data which have a lot of irregularities and peaks [12]. Hence we are motivated to develop a method that determines not only the discontinuities in smooth functions but the discontinuities in successive irregularities.

The approach in this paper offers significant advantages on the possibility of three dimensional trajectories and on the order of accuracy. Specifically, geometric measure of curvature and polynomial approximation on projected plane are used to identify derivative discontinuities. The method described here has threshold to determine the limit of curvature (i.e. the sharpness) so that a point has smaller than threshold could be considered as a discontinuity.

Our new technique can be described as one that successively locates derivative discontinuities by short time window in iterated integrals of the trajectory data.

II. Discontinuity Calculation Algorithm

In this method, firstly 3D trajectory data are decoupled into XY, YZ, and ZX as 2D plane. The projected planes are based on the matrices for orthogonal projected plane to perform a parallel projection from 3D data as follows [for more detail, see Computer Graphics by Hearn & Baker, p.438~442].

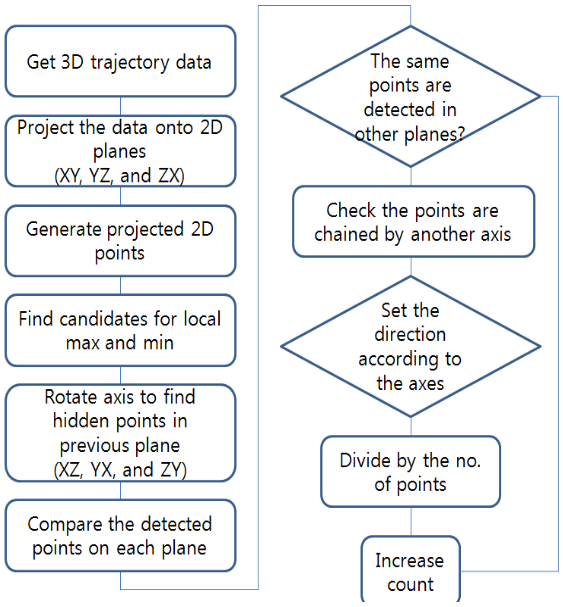


Figure 1. Discontinuity detection algorithm.

Next, the algorithm tries to find the candidate of local maxima and minima on each plane by high order derivatives (refer Fig. 1). More detail mathematical model will be described following section. In this step, we can get a lot of candidates varying on the threshold. The range of threshold had been changed from 0.001 to 0.007 by computational way. The best fitted threshold value is selected by comparing the number of detected points between visual evidence and detection program.

$$\mathrm{Mp} = \begin{bmatrix} 1 & 0 & L1\cos\phi & 0 \\ 0 & 1 & L1\sin\phi & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (1)$$

Therefore, the value which has the smallest distance value between both is the best fitted threshold value. Consequently, the value is approximately 0.003 or between 0.0025 and 0.003 (not optimal but suitable). However, by observation with 100 pre-sampled data comparison, the threshold value is set as 0.003 for more simplicity.

There are still hidden points which are not detected by the first independent axis projection. If trajectory is mostly parallel to un-decoupled axis (e.g., XY projected plane and the points which move along Z axis), the projected method doesn't detect the points along the axis. Therefore, we compute another projected plane along each projected axis. That means once a projected plane is generated, the axis has to be rotated 180 degree with respect to the reference axis to see and calculate the local max and min with respect to the reference axis. For example, if we get XY projected plane by decoupling at previous step, we can't see the any movement along Z axis because the axis is parallel to our eye. So we need 180 degree rotation with respect to X to see the trajectory on XZ.

Next, we compare each detected points to check if they are connected to each other like chain. By observation of our VE simulated trajectory data, any sharp movement is usually coupled by two axes such as XY and ZY. Of course some cases have three axes. For considering this kind of case, a kind of chain rule is applied to define the trajectory direction and avoid duplication in counting the number of discontinuity.

Therefore, the detected points are actually double in two projected planes but in reality the point affects only ZY plane. As a result, the number of detected point is regarded as one. The same rule is applied to other planes. Consequently, all detected points are synthesized through 6 planes (means twice), and the total detected number is divided by the number of duplicated number of points within two planes (here divided by 2). Finally, the number of points is registered as the number of discontinuity.

III. Derivative Discontinuity Detection Method

We assume that a sequence of trajectory data may be continuous and differentiable. It is based on a direct visual observation of the sampled data. Consider the following piecewise smooth data model.

$$x(t) = \sum_{i}^{k} U(t - t_{i-1}) f_i(t - t_{i-1}) \qquad (2)$$

where $U(\cdot)$ is the unit step function and where each $f_i(t)$ is a piecewise smooth segment. $x_1, x_2, \ldots, x_k$ are obtained at equally spaced points t_i (in our environment, the frequency is 60 Hz) The irregularities of x, could be called change point, occur at times t_i, $j = 1, 2, \ldots, k$, where k is unknown.

We set $t_0 = 0$ as a start point. Based on the observation, we can also set

$$y(t) = x(t) + e(t) \tag{3}$$

where $e(t)$ is an additive error terms such as noisy. We want to detect the change points and estimate their locations at time t_i. To model changes at one of its derivatives, let T be given and assume that there is at most one discontinuity point in each interval

$$I_\kappa^T = (\kappa - T, \kappa), \quad \kappa \geq T \tag{4}$$

In the sequel, we can set

$$x_\kappa(t) = x(t + \kappa - T), \qquad t \in [0, T], \quad \kappa \geq T \tag{5}$$

Then, we can redefine the discontinuity point, say t_κ, relatively to I_κ^T with

$$x_\kappa(t) = f_\kappa(t + \kappa - T) + \zeta \Theta_\kappa(t + \kappa - T) \tag{6}$$

where κ is change point, ζ is threshold of the change in the $(p-1)^{\text{st}}$ derivative.

$$\Theta_\kappa(t) = \begin{cases} t^{p-1}/(p-1)! & t > 0, \quad 0 < p \leq 2 \\ 0 & otherwise \end{cases} \tag{7}$$

f is a smooth function with at least p derivatives. If $p = 1$, $x(t)$ has a discontinuity at κ and if $p = 2$, $x(t)$ is continuous but has a discontinuity in its first derivative at κ. Note $\Theta_\kappa(t)$ could be changed into similar forms such as e^{-t_κ}.

By using elementary differential algebraic operations on this equation, the result backs in the time domain and we can get that t_κ is identifiable with respect to $x(t)$.

Finally, for a given finite set of $\{x_1, x_2, \ldots, x_m\}$ of fucntion defined on the interval $[I_a^T, I_b^T]$ (simply $[a, b]$), *MM* (MaxMin) is defined as

$$MM(x_1(t), x_2(t), \ldots, x_m(t)) = \begin{cases} \min_i x_i(t), & if\ x_i(t) > 0 \\ \max_i x_i(t), & if\ x_i(t) < 0 \\ 0, & otherwise \end{cases} \tag{8}$$

The MM (MaxMin) definer was applied to relax the resolution requirements as well as to reduce the significance of threshold parameters, although some thresholding techniques are still required for large variation. This MM (MaxMin) definer enables successful detection of discontinuities that are closely located as well. In the derivative discontinuity detection method, applying this MM definer also helps to minimize the effects of the oscillations. See Fig. 2:

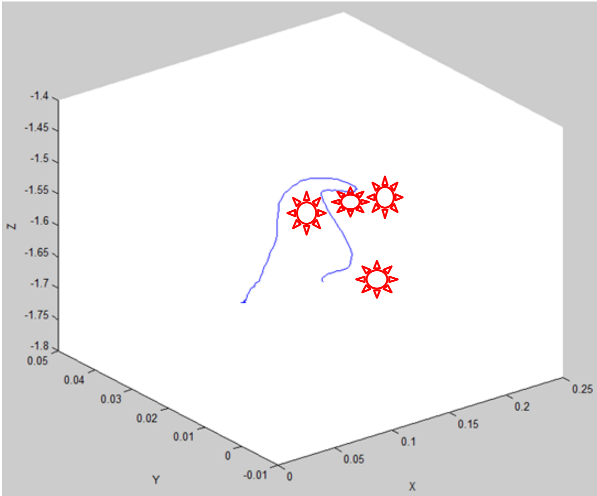


Figure 2. An example of 3D trajectory in VE. 10th trajectory in 75 degree rotation of pitch with 133 length of data sequence from subject #2.

IV. Experimental Results

In this section, we demonstrate the discontinuity detection algorithm with three dimensional teleoperation data sets in virtual environments.

A. *Experimental Conditions*

We designed 10 different axis rotation conditions for each axis (i.e., roll, pitch and yaw). The task is to touch the target sphere in three dimensional spaces (see Fig. 3).

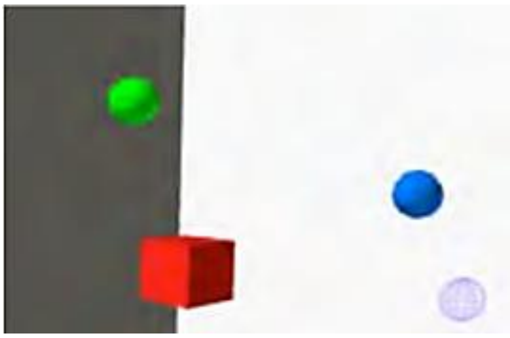
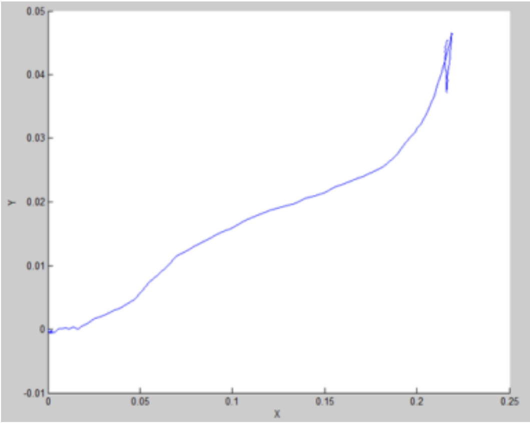
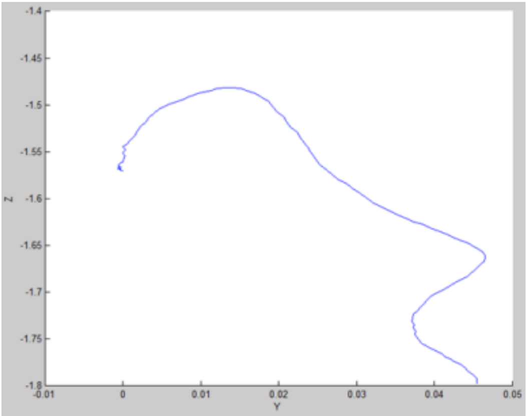


Figure 3. Screen shot of the environmental elements. The blue ball, user's hand held cursor that was used to move and touch the target object (green).

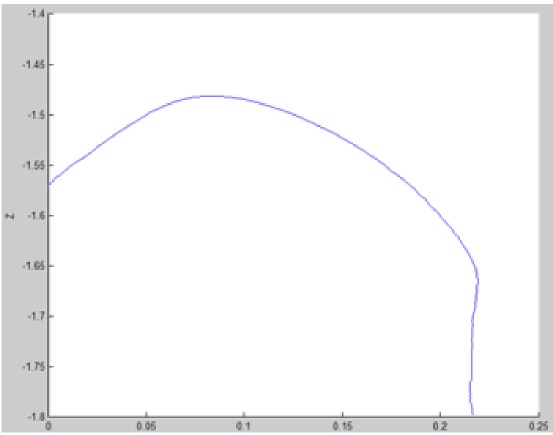
The experimental VE created for the study was a simple room with dimensions roughly matching the actual room (4.0 x 4.5 x 2.9 m) in which the experiment was conducted. Some realism was provided by texture mapping the ceiling and ground planes to roughly correspond to those in the physical room. Diffuse lighting coming from virtual room ceiling mimicked the lighting in the real room [3], [6].



(a) XY plane



(b) YZ plane



(c) XZ plane

Figure 4. Examples of projected planes.

The purpose of the experiment is to examine the difficulty of teleoperation tasks when an operator must use cameras which are not properly positioned during remote control of robot arms (see Fig. 4).

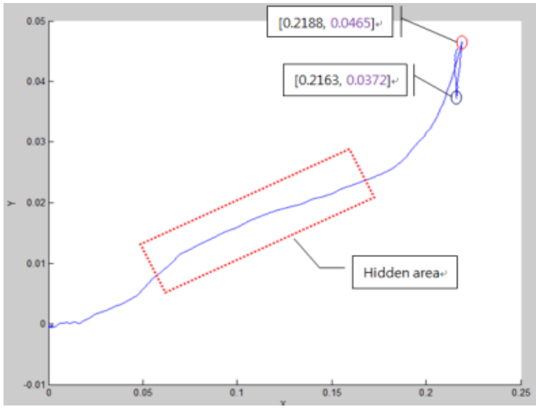
Under such circumstance, if camera is rotated to inappropriate direction, the operator's inputs to move the robot arms to user's desired direction might cause severe errors or accidents. The basic task is to use hands to control a small blue ball (i.e., three dimensional cursor) to move smoothly from a starting point in front of subjects to touch the target which is lager green ball which will randomly appear in various positions. Test consists of 10 blocks and each block has 3 warm-up trials and 7 experimental trials. A block has the same rotation degree for 10 trials.

The amount of rotation degrees varies from 0 to 180 degrees. Experimental sequence for each subject is randomized and each subject has a familization phase before data gathering experiments (refer [1] for detail explanation).

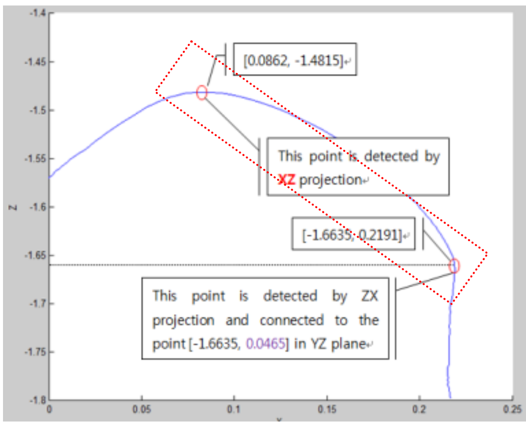
B. *Discontinuity Example*

We first set the threshold value to refine the discontinuity that we want to find. Fig. 2 shows an example of the discontinuities. As mentioned in previous section, threshold is set based on the observation of data sets which were randomly chosen from subjects' data pool.

There are three or four possible candidates for discontinuity (marked with red star). The proposed algorithm first decouples into three projected plane such as XY, YZ, and ZX (see Fig. 4).



(a) XY plane



(b) XZ plane

Figure 5. Red rectangle shows hidden area which there might be change points.

Once the candidates are extracted from XY-plane, the plane rotated towards XZ plane to see the hidden candidates (for example, the points probably move along Z axis). When we rotate the plane, it shows another important view for detecting discontinuity (see Fig. 5). As shown in Fig. 4, there are hidden change points and our algorithm can detect the hidden points by rotating the plane with respect to the reference axis (i.e., here x axis). Note that our method depends on the sequence of rotation or projection. Therefore, we have to synthesize the points which are detected by two planes. The same way is applied to other planes (see Fig. 6).

In our method, the detected candidates are chained (see Fig. 5 and Fig. 6). For example, point (-1.6635, 0.2191) detected by ZX plane is connected to the point [-1.6635, 0.0465] in ZY plane. In this case, the z value -1.6635 is reference point and Z axis is reference axis. Therefore, X and Y value is considered as that the movement was abruptly changed from X to Y or vice versa. As a result, the points are coupled to one discontinuity.

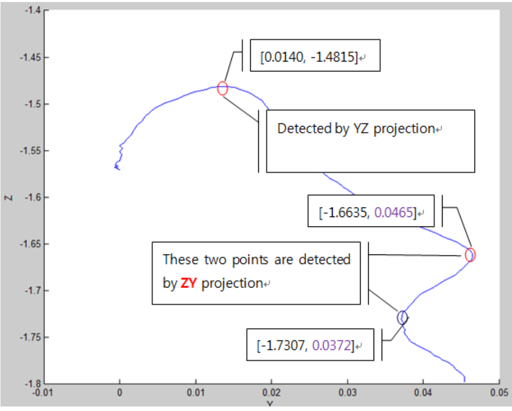


Figure 6. YZ projected planes.

C. *Real Experiments Data Analysis Results*

The data had been gathered approximately for three months and 18 subjects participated in the experiments. Each subject performed 300 trials (100 trials per each axis rotation) and the data are collected with 60Hz frequency. Fig. 7 shows overall results for the experiments.

Fig. 8 shows individual experimental results according to the with respect to the rotational strategy such as roll, pitch, yaw distortion.

The differing effects of roll versus pitch or yaw axis was checked in a nonparametric analysis in which each participant's peak Movement Time across all rotations was ranked by Axis of Rotation. Participants' maxima were generally among rotations between 90 ° and 140 °.

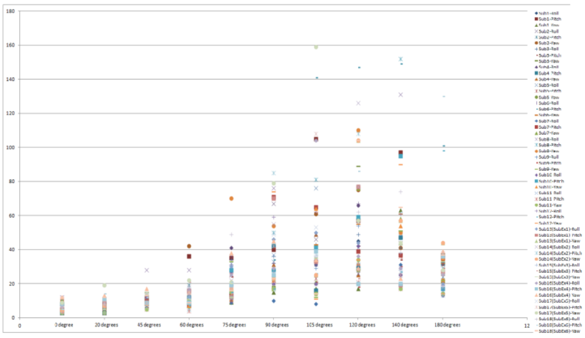
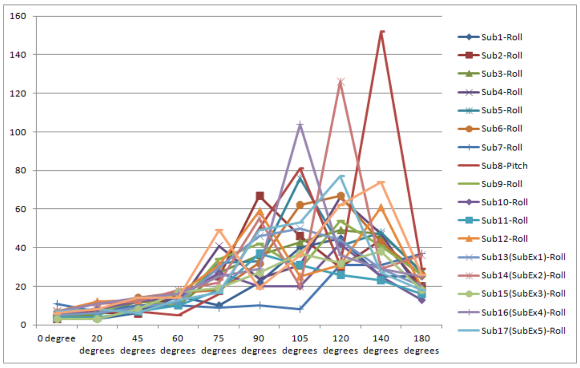
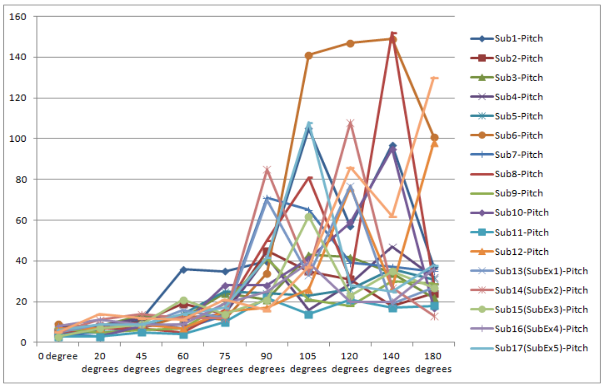


Figure 7. Overall discontinuity distribution.

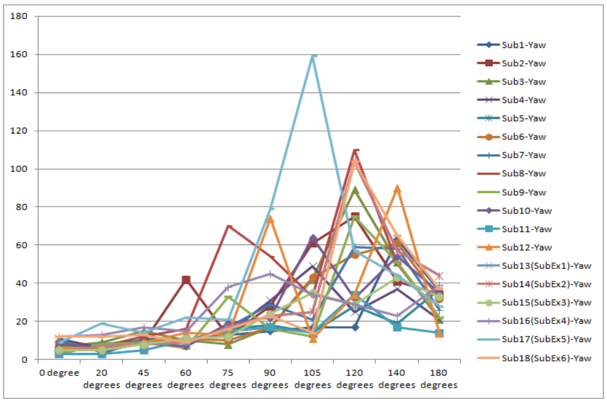
As shown in Fig. 8, abrupt changes happen according to the amount of the rotation until the degree of distortion approaches around 120 degree. Then, it shows a general pattern in abrupt transition that the user's errors decrease from 120~140 degree.



(a) Roll rotation



(b) Pitch rotation



(c) Yaw rotation

Figure 8. Results of each axis rotation.

V. CONCLUSIONS

This paper contributes the discontinuity detection algorithm using the projected plane and derivative method. The proposed approach provides a simple and exact method for detecting and calculating the discontinuity in three dimensional trajectory data. We have demonstrated this algorithm on real world data sets as well.

This algorithm provides the unique capability to determine the number of discontinuities and locations in the derivatives of a polynomial function on projected planes.

Discussion of rotation axis anisotropies naturally leads to consideration of what are the most representative rotation parameters. Due consideration of the general nature of rotation immediately leads to the observation that besides the amount of rotation, the orientation of the rotation axis could a key model parameter to predict behavioral effects of rotations in general.

One of the benefits of the proposed method is that it is applicable to single and multi-dimensional scattered data. Our future investigations include developing much simple, fast, exact and robust detection method using three dimensional vector analyses and comparing it to the method described here.

However, this research should be improved in that the method which is separate analysis might be integrated with some kinds of mathematical theories.

Conflict of Interest

The author declares no conflict of interest.

Author Contributions

The author conducted the research by himself.

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