ISSN Cetak 2745-925X
ISSN Online 2722-273X

JESSI Volume 03 Nomor 1 May 2022

FEATURES SIMPLIFICATION USING CUBIC BEZIER PROPERTIES FOR GAIT RECOGNITION ON SMARTPHONE

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Received : 22 Jan 22
Accepted : 30 Apr 22
Published : 10 May 22

Abstract

Abstract*: Smartphone is widely used around the world. It's user authentication usually used pin code, pattern code, fingerprint and conventional login authentication. One of authentication method which is non-intrusive during data collection is authentication by using gait. This mechanism classified as non-intrusive because this mechanism could gather biometric data without being noticed by the authentication subjects. Since it is non-intrusive, this mechanism allows re-authentications without bothering the authentication subjects. One of the recent gait recognition is using accelerometer on smartphone to measure and capture acceleration data on gait. This method extract step cycles in various length, map and interpolate the data into higher sample count, and then use each of mapped and interpolated data as feature using recognition. Regardless the classification or recognition method, using each mapped and interpolated data as features would result in high processing time during classification or recognition due to high feature count. In this research, we try to simplify the features of gait data with minimum data loss so it might give robust result with less latency by aligning cubic Bezier curve to step cycle data and extracting the Bezier properties.*

Keywords*: User Authentication, Gait Recognition, Smartphone, Accelerometer*

Abstrak

Smartphone banyak digunakan di seluruh dunia. Ini adalah otentikasi pengguna biasanya menggunakan kode pin, kode pola, sidik jari dan otentikasi login konvensional. Salah satu metode otentikasi yang tidak mengganggu selama pengumpulan data adalah otentikasi dengan menggunakan gaya berjalan. Mekanisme ini tergolong non-intrusif karena mekanisme ini dapat mengumpulkan data biometrik tanpa diketahui oleh subjek otentikasi. Karena tidak mengganggu, mekanisme ini memungkinkan otentikasi ulang tanpa mengganggu subjek otentikasi. Salah satu pengenalan gaya berjalan baru-baru ini adalah menggunakan akselerometer pada smartphone untuk mengukur dan menangkap data akselerasi pada gaya berjalan. Metode ini mengekstrak siklus langkah dalam berbagai panjang, memetakan dan menginterpolasi data ke dalam jumlah sampel yang lebih tinggi, dan kemudian menggunakan masing-masing data yang dipetakan dan diinterpolasi sebagai fitur menggunakan pengenalan. Terlepas dari metode klasifikasi atau pengenalan, menggunakan setiap data yang dipetakan dan diinterpolasi sebagai fitur akan menghasilkan waktu pemrosesan yang tinggi selama klasifikasi atau pengenalan karena jumlah fitur yang tinggi. Dalam penelitian ini, kami mencoba menyederhanakan fitur data gaya berjalan dengan kehilangan data minimum sehingga dapat memberikan hasil yang kuat dengan latensi yang lebih sedikit dengan menyelaraskan kurva Bezier kubik ke data siklus langkah dan mengekstraksi properti Bezier.

Kata kunci: Otentikasi Pengguna, Pengenalan Gaya Berjalan, Smartphone, Akselerometer

1. Introduction

Smartphone is widely used around the world. It's user authentication usually used pin code, pattern code, fingerprint and conventional login authentication. This kinds of authentication mechanism is intrusive because those mechanisms requires users to give exclusive interaction for user authentication during the process. If users are failed to authenticate themselves, they need to repeat the process so that they can use features in their smartphone. This kind of authentication also only use single authentication to validate access for a long time [1]. If it only validate access for a short time, it would make users uncomfortable due to exclusive interaction requirement.

One of authentication method which is non-intrusive during data collection is authentication by using gait. This mechanism classified as non-intrusive because this mechanism could gather biometric data without being noticed by the authentication subjects. Since it is non-intrusive, this mechanism allows re-authentications without bothering the authentication subjects. With such properties in this mechanism, it could be used to detect data spoofing on smartphone [2] or early smartphone theft detection.

Some researches uses image sequence or attaching sensors on parts of human's body [3] [4], [5] to capture the gait data. Those setups cannot be applied on detecting smartphone theft because those methods require a certain set up of the devices. One of the recent gait recognition is using accelerometer on smartphone to measure and capture acceleration data on gait [6]. This method extract step cycles in various length, map and interpolate the data into higher sample count, and then use each of mapped and interpolated data as feature using recognition.

Earlier gait recognition done by capturing gait data using optical sensors. Optical sensors capture sequence image of a person during a walk and then extract features to indentify who is walking. Several features are used to identify the gait such as hand swing, knee swing, heel strike, etc. Since it is using optical tsensors, image resolution generated by sensors affect the result significantly [2]. This causes some researchers think another way to obtain gait data using other sensor such as accelerometer and gyroscope sensor [5].

Gait recognition using accelerometers is a relatively new topic in biometric. Earlier studies uses accelerometer and gryoscope with sample rate 100Hz or above[2] [5] [6]. Those studies used several Inertial Measurement Unit attached to several parts of user's body. These high data resolution sensor are not widely used and since it's worn in several part of body, it might give slight uncomfortable feeling to user.

Accelerometers which is widely used are accelerometers embedded in smartphone. The problem is accelerometer on smartphone's sample rate is much lower than IMU's. A recent study done by Ren [6] uses only smartphone's accelerometer with 50Hz sample rate for healthcare system gives quite robust result. Their method uses weighted Pearson Classification to compare gait data and Support Vector Machine to classify the gait data. They used each sample from normalized gait data (300 samples in their paper) as features for recognition. In this research, we try to simplify the features of gait data with minimum data loss so it might give robust result with less latency.

Regardless the classification or recognition method, using each mapped and interpolated data as features would result in high processing time during classification or recognition due to high feature count. After observing several accelerometer's gait data, we notice that there are several significant extrema which are similar for step cycles recorded from same person but still distinct for each person. From that observation, we have an idea to align a Bezier curve with step cycle data between those extrema. In this paper, we try to simplify the feature count by generating Bezier curve and

JESSI
Journal of Embedded System Security and Intelligent System
ISSN Cetak 2745-925X
ISSN Online 2722-273X
JESSI Volume 03 Nomor 1 May 2022

using the anchor and control points of the Bezier curve as features.

2. Research Methods

Our method generally follows 4 general steps as shown in Fig. 1.

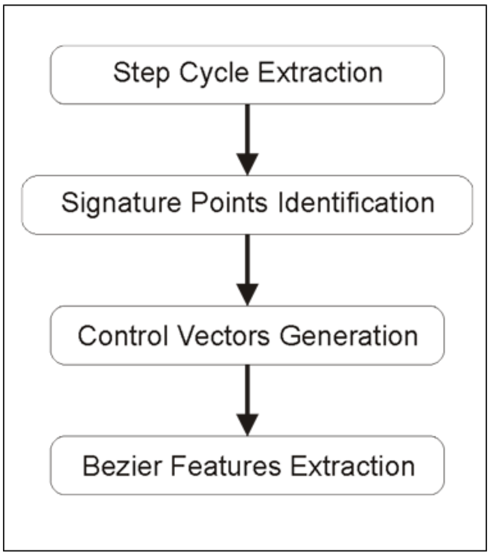

Figure 1. General flow of Cubic Bezier Properties Extraction.

3. Result

First is step cycle extraction. In this step we use same method as used by Ren [1] since their step extraction using Pearson Correlation Coefficient is quite fast and simple.

Second step is signature point identification. In this step we normalize and convert the step cycle data to τ radian format. After normalization and conversion, we identify signature point (SP). SPs are selected from several extrema and end points that was retrieved from step cycle data. Extrema which are qualified to be SP are those extrema which has range more than a certain threshold to previous extrema.

Third step is generating control vectors ($(\overrightarrow{CV})$) for Bezier curve. In this step, we treat each SP as anchor point to bezier curves. Each line segment between a SP and next SP has two control points. Before getting the control point, we need to find the base control vector. To find a control vector, first we form a line segment between two SPs. Second, we classify step data between SPs according its position whether the data is above the line or below the line. If all of the data are in the same side of the line, we seek the furthest data from the line and define the position relative to each SP as base control vector ($(\overrightarrow{BCV})$). If data is scattered to area above and below the line, we find the furthest data for each side. The position of those furthest data relative to nearest SP would become the base control vector of respective SP.

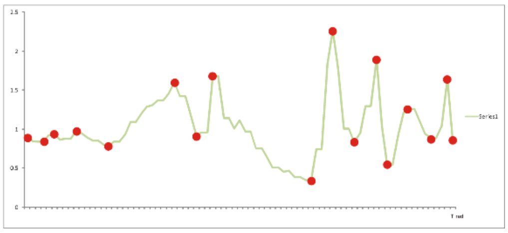

Figure 2. Signature Points of a step cycle data.

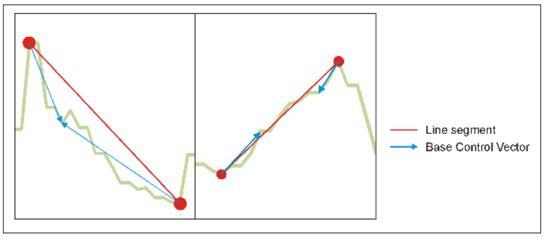

Figure 3. Example of obtaining Base Control Vector

After we got the $(\overrightarrow{BCV})$, we multiply the each vector to a coefficient to obtain $(\overrightarrow{CV})$. Coefficient for each vector is calculated by involving the magnitude ratio of BCVs in a line segment. We do not need to generate the Bezier curve but if we interpolate the data between two SP using Cubic Bezier Interpolation, we will got a curve which look like a regression of step cycle data.

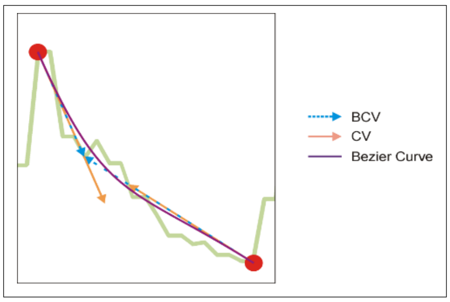

Figure 4. Control Vector and Bezier Representation

JESSI
Journal of Embedded System Security and Intelligent System
ISSN Cetak 2745-925X
ISSN Online 2722-273X
JESSI Volume 03 Nomor 1 May 2022

Once all SP and (CV) ⃗ identified, we can progress to the last step, feature extraction. From Fig. 5, it is clear that each SP and (CV) ⃗ are the features of Bezier curve that aligned to step cycle data. With those features in mind, we decompose the properties of each SP as illustrated in Fig. 6.

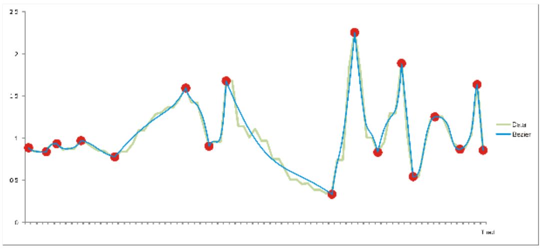

Figure 5. Bezier Generated From Step Cycle Data

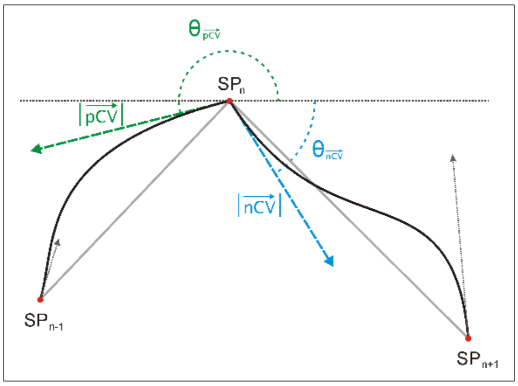

Figure 6. Properties Decomposition of each SP

4. Conclusion

We decompose each SP to five properties. First is the coordinate of each SP on normalized step cycle data. The rest are properties obtained by decomposing (CV) ⃗s which are directly associated with the SP. Other than the first and last SP, each SP directly associated with two (CV) ⃗s. We define (CV) ⃗s which are connecting to previous SP as (pCV) ⃗s and (CV) ⃗s which are connecting to next SP as (nCV) ⃗s. We use magnitude and direction of each (CV) ⃗ as properties of an SP. Thus the rest four properties are magnitude of (pCV) ⃗ or |(pCV) ⃗ |, direction of (pCV) ⃗ or θ_(pCV) ⃗, magnitude of (nCV) ⃗ or |(nCV) ⃗ |, and direction of (nCV) ⃗ or θ_(nCV) ⃗. In current example, step cycle data contains 80 samples and we could generate 17 SPs. With each SP have five properties excluding the first and last SP which has three properties, the feature count that could be extracted from this example is 81. Comparing to Ren [1] which used 300 features, our method could reduce the feature count to less than a third.

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