

題目：論文標題

Title：Thesis title

姓名：王茗琛
Name
學號：2230025907
StudentNo.
學院：創新工程學院
Faculty
課程：智能技術碩士
Program
專業：智能技術碩士
Major
指導教師：劉新
Supervisor
日期：YYYY/MM/DD
Date

摘 要

本文研究離散事件繫統的監督控制問題。在使用該範本中有任何問題請聯繫覃濤 zhwli@ieee.org。澳門科技大學系統工程研究所感謝覃濤對設計此範本的貢獻。

The template can be used in online and offline ways. For the former (highly recommended), Overleaf(<https://www.overleaf.com>) is a collaborative cloud-based LaTeX editor used for writing, editing and publishing scientific documents, which is much easy to use and friendly. In overleaf, the compiling command is [XeLatex](#).

For the latter, one can use Texstudio, which is a very popular yet free software package (<https://www.texstudio.org/>). When using Texstudio, the compiling command is [XeLatex](#). To make Texstudio work, one need to first install [Mik-tex](#), see <https://miktex.org/>. We happen to find, rather rarely, that a successful compiling may depend on the version of Texstudio. In any case, we recommend the latest version of Texstudio.

關鍵詞：離散事件繫統; 監督控制; 故障診斷.

Abstract

This research deals with the supervisory control problem of discrete event systems.

Do not say something like “This paper”.

(Use singular keywords. Keywords are separated by commas or semicolons, and there is often a period at the end.)

KeyWords : Discrete event system; supervisory control; fault diagnosis.

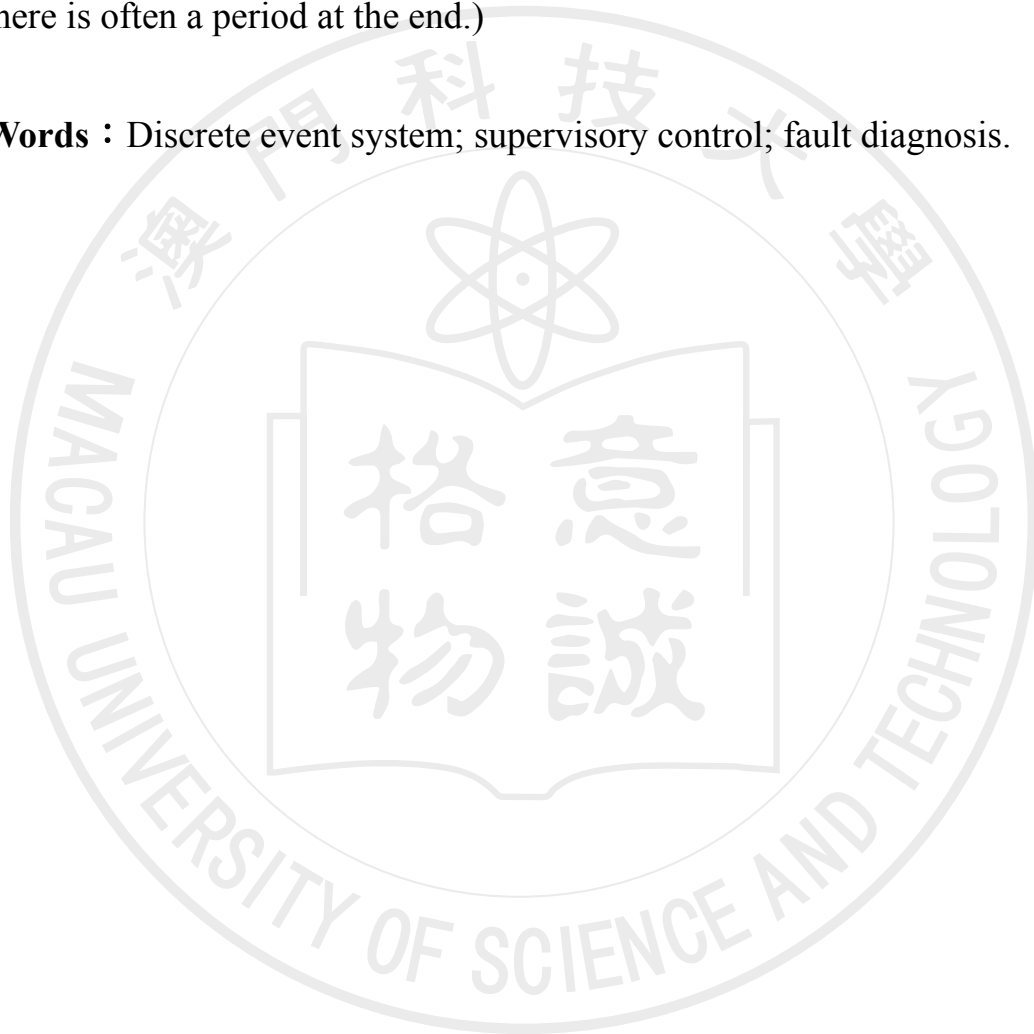


Table of Contents

摘 要	I
Abstract	II
Table of Contents	III
List of Figures	V
List of Tables	VI
List of Symbols	VII
List of Abbreviations	VIII
1 Introduction	1
1.1 Research Background	1
1.2 Research Motivation and Importance	3
1.3 Research Objects	7
2 Figures and Tables	9
2.1 Figures	9
2.2 An example of table	10
3 Research Method	11
3.1 Mathematical rigour	11
4 An example	13
5 Conclusions	14
References	15
Appendix	16
Acknowledgements	17

Resume	18
--------------	----



List of Figures

1.1 Thesis organization.	9
----------------------------------	---

If the logo of MUST disturbs your editing, it can be commented out. After the thesis is done, it can be exposed again.



List of Tables

2.1 Interpretation of transitions and places in Fig. 2.5	18
--	----



List of Symbols

P	Set of places
G	Deterministic finite automaton
G_{nd}	Nondeterministic finite automaton
δ	Partial state transition function
x_0	Initial state
X_0	Set of initial states
Σ	Set of events

Remark: Articles are not needed in a nomenclature. For example, the counterpart of Σ reads as “Set of events”, instead of “The set of events”, although an article “a” or “the” is grammatically necessary.

List of Abbreviations

Abbreviations	Full name in English
AMS	Automated Manufacturing System
DES	Discrete Event System



Chapter 1 Introduction

1.1 Research Background

Biometrics technology is a technology that identifies or verifies individuals based on their physiological characteristics such as fingerprints, face, iris, etc. or behavioral characteristics such as voiceprints and handwritten signatures. This technology is widely used in security authentication, financial transactions, access control systems and other security areas [1] for personal identification or verification. In the identification scenario, the system will identify the user profile already in the system database based on the physiological or behavioral characteristics provided by the user. This scenario is applicable to fingerprint, iris identification of personal identity, etc. Secondly, in the verification scenario, the user needs to provide the system with verified identity and characteristic information, and the system will judge whether the current user is the declared user based on the stored characteristic information and the information currently provided by the user, which is applicable to the scenarios of declaring personal identity and providing personal characteristic information, such as the unlocking of smart phones and international border crossing.

Handwritten signature is a more important individual behavioral characteristic in daily life, and as the main characteristic for verifying personal identity in legal, financial, administrative and other fields, because it cannot be intruded during the collection process, handwritten signature is also regarded as one of the main characteristics of many technologies for verifying personal identity. Handwritten signatures produce different writing styles, such as regular and cursive, depending on the individual's writing habits. Even with the passage of time, the personal writing style may change, and the signature (defined as Query) provided by the user after a certain period of time may differ from the reference signature (defined as Reference) previously entered into the system. As a result, there will be some difficulties in comparing the verification of the user's handwritten signature, for example, there will be differences in the angle of the bending strokes, the length of the straight line, and the hook at the end of each character on the per-

sonal signature. As mentioned above, the handwritten signatures may be slightly different in the end depending on individual writing habits. Therefore, in order to obtain a user's identity privileges, some people may maliciously forge handwritten signatures to pass the security and privacy checking system, or even practice for a long time in order to achieve handwritten signatures of similar styles as a certain user. As a result, academics have launched a series of studies on handwritten signature verification, hoping to design a relevant model to help relevant staff to more efficiently complete the process of more repetitive handwritten signature verification work, so that more staff to participate in the more core work.

In academia, handwritten signature verification is categorized into two types, offline and online, depending on the data collection route. The collection process of offline handwritten signatures is obtained after the user's writing process on paper; online handwritten signatures are collected by using a digitizing station, and the collected handwritten signature images may be affected by the equipment, such as the position of the pen, tilt, and pressure, etc. [3]. In addition to the different data collection routes are categorized into different types of handwritten signature verification, scholars have defined two types of branching tasks, Writer-Independent (WI) and Writer-Dependent (WD) to evaluate the model algorithms. The WI task refers to the modeling structure where a handwritten signature image is inputted, and the handwritten signature is verified based on the reference signature and the The WI task refers to the input of a handwritten signature image into the model structure, and based on the features extracted from the reference signature and query signature, it determines whether the query signature is forged or not, while the WD task adds the author id to the input of the WI task, and based on the author id, it uses the corresponding author classifier to determine whether the query signature is forged or not. These two branching tasks, although both output the label category of query signatures (genuine or forged) at the end, can reflect the different performance of the model to different degrees. The WI task focuses on learning the global characteristics of the signature population, does not need to learn a separate author classifier for each user, and has the excellent extensibility of not requiring re-training for new users, and at the same time can reflect the generalization and discriminative ability of the model. The WI task fo-

cuses on learning the global features of the signature group, does not need to learn an author classifier for each user individually, has excellent scalability without re-training for new users, and can reflect the model's generalization and discriminative ability; the WD task additionally trains an author classifier for each user individually, which can take into account the high accuracy of different styles of signatures of individual authors that are still considered to be real signatures, but needs to collect a sufficiently large number of samples for each user, with a high cost of training and a weak generalization ability. Thus the WI and WD tasks can reflect the overall performance of the model to different degrees, and the model performance is comprehensively evaluated according to the evaluation indexes of the two tasks.

With the development of the level of technology, the field of artificial intelligence has been able to generate fake pictures based on the sample images and keywords provided by the user, and it is difficult for normal people to identify the real and fake with the naked eye. Therefore, there will be part of the artificial generation of forged signature behavior, so as to achieve the fake to pass the verification of the security system, resulting in personal privacy, property invasion, theft and other dangerous consequences. Relying on manual power to verify will have certain social risks and judgment errors, so the study of offline handwritten signature verification, to a certain extent, can reduce the risk of forged signatures through the verification of the relevant algorithmic models to help minimize the error of manual verification, so as to better ensure personal privacy and property security.

1.2 Research Motivation and Importance

This paper focuses on the offline handwritten signature verification task, which is essentially a derivative branch of the image classification task. Unlike the traditional image classification task, the offline handwritten signature verification task requires the input of a pair of signature image samples from the REFERENCE and QUERY pairs, and the WD task requires an additional input of an author id to train an author-independent classifier. The offline handwritten signature verifica-

tion model will extract relevant image features based on the input reference and query signature images, and compare the features to output genuine or forged category labels. Thus the task is challenging and innovative, the design of the model or algorithm architecture not only needs to consider the criticality of the model to extract a pair of image features, the model architecture of the isotropic dual-stream will directly affect the criticality of the features extracted from the reference signature and query-signature images, and once the extracted features don't have so important information, it will lead to a drastic decrease in the model's ability to make judgments. At the same time, due to the definition of the WI and WD tasks and the real-life application scenarios, it is required to have a high accuracy rate and generalization ability to prevent personal privacy and property infringement, but also to enhance the demand for the performance of the model, which makes the design and experimentation of the offline handwritten signature verification model a very challenging image task.

In the design of offline handwritten signature verification model, it is divided into two parts: feature extractor and author classifier for WD task. In the past research of scholars, most of the data cluster features based on sample distribution and other data cluster features to manually design the image feature extraction method, to take the traditional machine learning approach to determine whether the signature is forged or not [1], such as taking the distance between the features or SVM to determine whether the signature is forged or not. But this manually designed features have the defects of specific data clusters, it must require the data set of the author's signature style uniformity, subtle differences will be as outliers leading to the traditional machine learning methods to determine the accuracy of the decline in the accuracy of the work, but the actual production work is required to have these certain differences in the tolerance of the degree of the work, so this method of extracting the features to take the artificial design is gradually phased out. Scholars hope to have an image feature extractor that focuses more on a certain part of the image and does not need to intervene many times. With the rapid development of deep learning in the past six years, convolutional neural network (CNN) with shared parameters for local field of view operations has achieved good results in traditional image classification tasks such as MNIST, ImageNet,

and compared with the traditional machine learning methods, the accuracy and generalization ability of CNN is even better than that of traditional machine learning methods. The accuracy and generalization ability of CNNs have been further verified in comparison with traditional machine learning methods. As a result, scholars in the field of handwritten signature verification have introduced CNN as a feature extractor, and experiments have proved that the accuracy and generalization ability of this approach has made a great breakthrough compared with previous methods [2].

Even though CNN's ability to extract image features is outstanding, its core idea of convolutional kernel operation has a certain local field of view reinforcement learning ability, which can focus on the local features of the image; however, for handwritten signatures not only need to pay attention to the degree of the corners of the font strokes, but also need to pay attention to the overall style of the signature image, fonts, and other factors, which may result in the case of the signature of the same author in a different location, so CNN as a feature extractor still has some defects. With the development of the field of natural language processing, the appearance of Transformer [9] with global feature learning attracted the attention of scholars, and then scholars in the field of image introduced the Encoder-Decoder architecture of Transformer for experiments on classification tasks [?]. The experiments proved that this approach outperforms CNN's feature extractor in the case of model parameter convergence, but the training conditions to reach model parameter convergence are more demanding because Transformer's attention mechanism needs to learn the whole image, whereas CNN adopts the way of sharing parameters to learn the local features of the image, so that the model convergence can be reached more quickly, but in the practical use, the generalization ability is poor. However, in practice, the generalization ability is poor, and the dataset needs to be constantly fine-tuned to achieve higher model performance. As a result, CNN is derived as Backbone to extract multi-channel feature maps, which are flattened as feature vectors and entered into the Transformer to perform global attention feature operations [?] In order to achieve the multi-channel feature map in the absence of overall information, after the Transformer's attention mechanism to strengthen the characteristics of the overall information, experi-

ments have proved that this way can be more effective in learning image features, models and thus achieve better accuracy and generalization ability. In summary, the CNN+Transformer style model architecture has become a mainstream framework in the image field in recent years, and it has also been introduced in offline handwritten signature verification tasks, and experiments have proved that this style of model architecture has a good model performance[?] Therefore, the offline handwritten signature verification model based on Transformer proposed in this paper is also a CNN+Transformer style model architecture, which conforms to the development trend of this field in deep learning in recent years, and adds multi-scale fusion features based on it, so that it can learn the signature image at multiple scales while meeting the increasing requirements of high-definition image resolution. The features such as font stroke corners make up for the shortcomings of multi-channel feature maps in terms of scale after CNN. In the final output classification stage, unlike the traditional image classification task, the model proposed in this paper will collect the features from previous modules in the final output, and perform overall stitching for category label prediction or model training, which has been proven to be effective [?]. . The challenge of this research is how to effectively use multi-scale fusion features for category prediction and model training. This way of training and prediction using the overall model features can better train the model weights of each part of the model as a whole, and the model training to the convergence stage will surpass most of the previous deep learning model architectures, and it provides a novel idea for the related fields to integrate the feature approach of convolutional neural networks and attention mechanisms. For related fields, it provides a novel idea to integrate the features of convolutional neural network and attention mechanism, which provides a certain design idea for the subsequent more concise fusion module; on the contrary, this approach will increase the computational reasoning pressure of the equipment and the cost of model training, which needs to be proved to be effective through a variety of experiments.

1.3 Research Objects

The OSVTF architecture proposed in this paper, as a whole, is a model designed based on the idea of twin networks, as shown in Fig. 1.

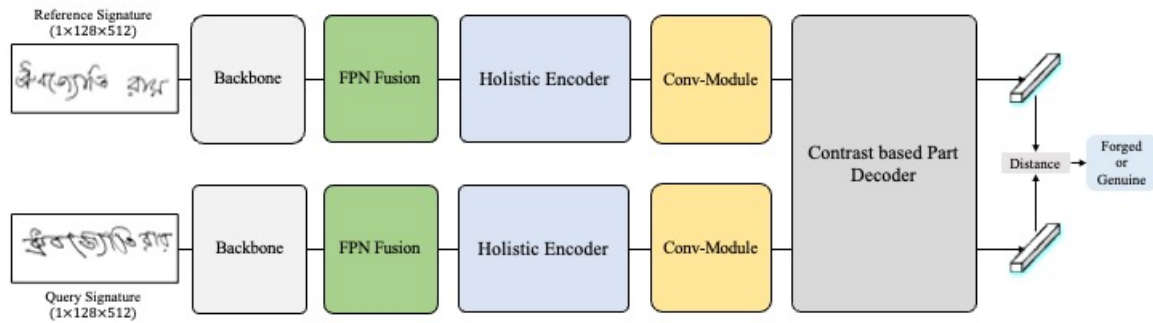


Fig. 1.1: OSVTF Structure

The core idea of a twin network is two sub-networks with shared weights that accept two inputs and output two feature vectors, and subsequently use a distance function to compute the similarity [?]. In the WI and WD tasks of offline handwritten signature verification, a pair of images of the input reference and query signatures are input, so the overall architectural aspect is referenced from TransOSV [?]. On the basis of TransOSV, backbone and FPN Fusion modules are added, and a series of optimizations and adjustments are made to Encoder, Conv-Module and Decoder, which are more conducive to the change and learning of the features of each part, and the experimental part needs to confirm that these modules can improve the model's ability to judge forged signatures and generalize the model to different scenarios. Experimentation In the overall research plan and experiments, the two general directions of WI and WD are still adopted to evaluate the model performance and quality, based on which the multi-channel feature map of CNN and the attention mechanism of Transformer will be visualized, and it is necessary to pay attention to whether these modules are able to

better grasp the important feature information of the image in the learning of image features. In addition, there are various ways of fusion of multi-scale features, such as Mask-RCNN [?]. The Feature Pyramid Network Style (FPN-Style) [?] is adopted. , this fusion approach includes but is not limited to mean accumulation, direct summation, and splicing, so these fusion approaches will be followed by model training with control variables to obtain the best performance fused multi-scale feature map approach. In addition, the previous twin network approach is based on the distance function to calculate the similarity to complete the related tasks, whether this approach can still be effective after the addition of multi-scale fusion of features needs to be verified to some extent, this paper will refer to the traditional image classification task of the classification of CNN processing, the addition of a global average pooling layer as a classifier to classify the features of the classification label prediction, so as to determine whether it will be better than the previous distance similarity judgment. In summary, this paper will be divided into three parts of the research phase: 1. Initially, the OSVTF model architecture will be trained in the model cycle to verify whether the optimization and adjustment scheme of the multi-scale features and model can be improved on the original architecture; 2. For the multi-scale fusion method of the FPN Fusion module, a small fine-tuning training will be taken on the basis of the first phase by adopting the control variable method for the model, and the optimal multi-scale feature fusion method will be screened out. The best multi-scale feature fusion method; 3. For the WI task, a global average pooling classifier is added in the final classifier stage, which is compared with the previous method of distance similarity prediction for offline handwritten signature verification, so as to judge the advantages and disadvantages of the two classifiers, and a better classifier is adopted for experiments in the WD task to verify whether it works.

Chapter 2 Figures and Tables

2.1 Figures

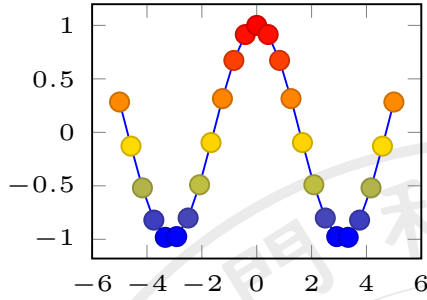


Fig. 2.1: A figure.

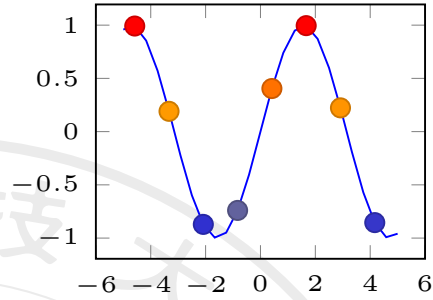


Fig. 2.2: Another figure.

Fig. 2.1 and Fig. 2.2 represent two figures. In what follows, we draw an automaton using \LaTeX . All the sizes of elements in a drawing can be controlled.

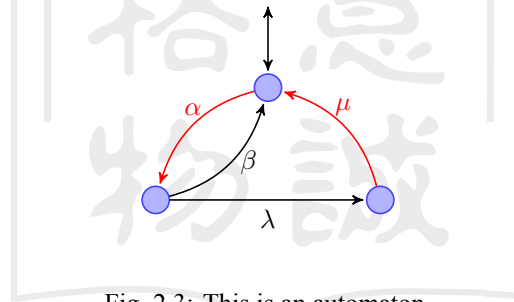


Fig. 2.3: This is an automaton.

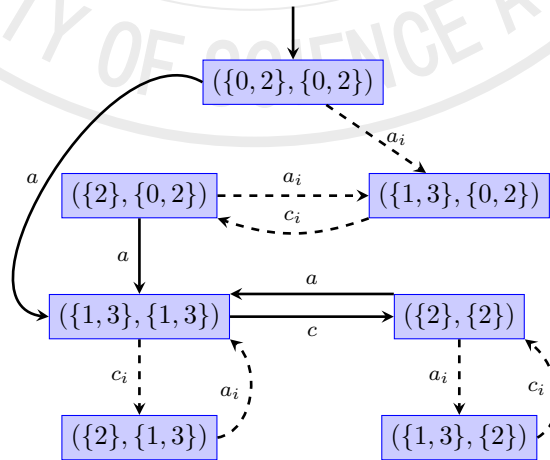


Fig. 2.4: Indicator automaton and verifier of the NFA in Fig. 2.3

2.2 An example of table

The table title is at the top of the table.

Table 2.1: A table.

Class ^a	γ_1	γ_2^b	$\langle\gamma\rangle$	G	$ f $	θ_c
BL Lacs	5	36	7	-4.0	1.0×10^{-2}	10°
FSRQs	5	40	11	-2.3	0.5×10^{-2}	14°

Table 2.2: Another table.

i	x_i	n_i	i	x_i	n_i
1	0.5~0.64	1	8	1.48~1.62	53
2	0.64~0.78	2	9	1.62~1.76	25
3	0.78~0.92	9	10	1.76~1.90	19
4	0.92~1.06	26	11	1.90~2.04	16
5	1.06~1.20	37	12	2.04~2.18	3
6	1.20~1.34	53	13	2.18~2.38	1
7	1.34~1.48	56			

Chapter 3 Research Method

Our approach is based on ...

The next step is to use mathematical formulas. The format of mathematical formulas is as follows.

3.1 Mathematical rigour

形式化是數學嚴密性的主要內容, 簡單地說, 形式化就是符號化。

公式的運用十分重要!

公式：式子居中，編號靠右。

Example 1:

$$e^{\pi i} + 1 = 0 \quad (3.1)$$

Example 2:

$$a^2 + b^2 = c^2 \quad (3.2)$$

If no equation number is needed, we can use double dollars at the beginning and end of the equation.

$$\cos x + \sin y = 1.$$

Example 3:

$$\binom{n}{m} = \binom{n}{n-m} = C_n^m = C_n^{n-m} \quad (3.3)$$

Example 4:

$$(a+b)^3 = (a+b)(a+b)^2 = a^3 + 3a^2b + 3ab^2 + b^3 \quad (3.4)$$

Here are more examples of mathematics equations or expression.

$$x = a_0 + \frac{1}{a_1 + \frac{1}{a_2 + \frac{1}{a_3 + \frac{1}{a_4}}}} \quad (3.5)$$

$$\frac{(x_1x_2) \times (x'_1x'_2)}{(y_1y_2y_3y_4)}$$

$$P\left(A=2\left|\frac{A^2}{B}>4\right.\right)$$

$$M=\begin{bmatrix}\frac{5}{6}&\frac{1}{6}&0\\ \frac{5}{6}&0&\frac{1}{6}\\ 0&\frac{5}{6}&\frac{1}{6}\end{bmatrix}$$

$$\begin{matrix}x&y\end{matrix}$$

$$M=\frac{A}{B}\begin{pmatrix}1&0\\0&1\end{pmatrix}$$

$$f(n)=\begin{cases}n/2&\text{if }n\text{ is even}\\ -(n+1)/2&\text{if }n\text{ is odd}\end{cases}$$

$$\binom{n}{r}=\frac{n!}{r!(n-r)!}$$

Here are some logic expressions:

$$(\forall s \in \overline{K})(\forall \sigma \in \Sigma)(\forall s' \in \overline{K})s\sigma \in L(G) \ \& \ s'\sigma \in L(G) \ \& \ Ps = Ps' \implies s' \in \overline{K}.$$

For more details about mathematics equations or expressions, see <https://en.wikibooks.org/wiki/LaTeX/Mathematics>.

Chapter 4 An example

An example of the Algorithm 1.

Algorithm 1: identifyRowContext

Input: r_i , $Backgrd(T_i)=T_1, T_2, \dots, T_n$ and similarity threshold θ_r

Output: $con(r_i)$

```

1  $con(r_i) = \Phi$ ;
2 for  $j = 1; j \leq n; j \neq i$  do
3   float  $maxSim = 0$ ;
4    $r^{maxSim} = null$ ;
5   while not end of  $T_j$  do
6     compute Jaro( $r_i, r_m$ );
7      $con(r_i) = con(r_i) \cup r^{maxSim}$ ;
8 return  $con(r_i)$ ;
```

There are many sources for Latex editing, see <https://latexref.xyz/>.

Chapter 5 Conclusions

結論由研究結果引伸而來，相同的研究結果，不同的研究者可能引伸出不同的結果，作者可表達對此結果具有的理論和實際價值的看法，具體要求如下：

(1) 包括研究過程中所遇到或引發的種種現象思考、根據研究成果，提出解決問題的方向，以及未來值得研究的方向。

(2) 結論要根據論文寫出總結性內容，觀點需具體明確，要有自己的創見。

(3) 應直接回答研究問題。論據充分，層次清楚，觀點明確，要點分明，評論合理可信。提示進一步研究的問題，交待本研究是否具體可行，提示亟待改進之處，詳細地交待研究限制。建議應具參考價值。

Review the main research purpose or hypothesis, discuss whether the results meet the expectations, and briefly explain the reasons.

Summarize the main research results, discuss the consistency or inconsistency with other scholars' conclusions and the reasons.

Point out the limitations of the research and the possible impact of the limitations.

Point out the theoretical significance or potential engineering application value of the results.

References

- [1] M. Fang, “A journey to the west,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 1, pp. 23–45, 2019.
- [2] M. Wang, and S. Li, “A journey to the west,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 1, pp. 23–45, 2019.
- [3] L. Zhao, Q. Liu, and B. Yang, “A journey to the west,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 1, pp. 23–45, 2019.
- [4] L. Zhao, Q. Liu, and B. Yang, “A journey to the east,” in *Proc. IEEE International Conference on Systems, Man, and Cybernetics*, Bari, Italy, Oct. 2020, pp. 345–349.

References are ordered alphabetically by the first author’s last name. If the first item is the same, check the last name of the second author, and so on. If two papers shared the same author list, the paper first listed is the one published earlier.

Appendix

主要是冗長結論如定理的證明, 以及實驗中裝置的冗長描述及參數等。

A.1 An appendix



Acknowledgements

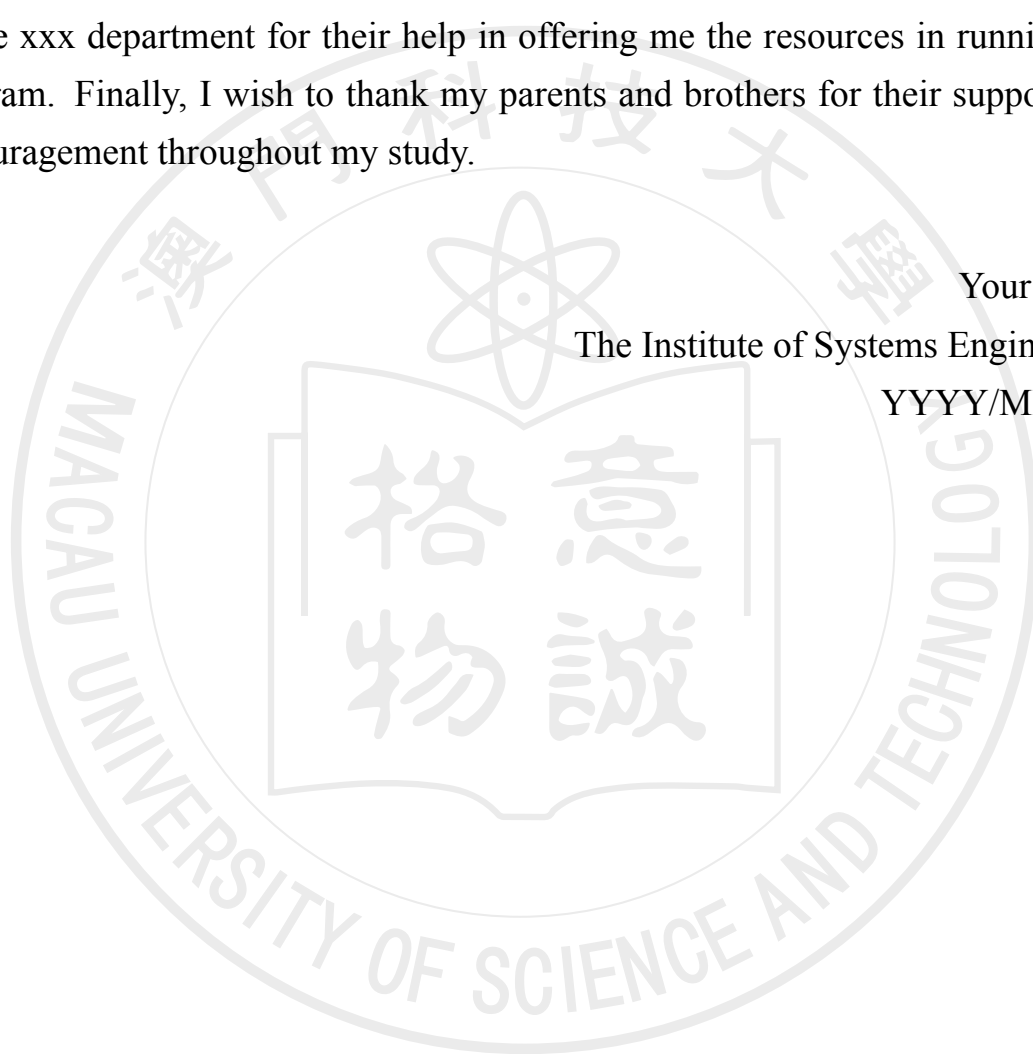
I would like to express my deep gratitude to Professor xxx and Professor xxx, my research supervisors, for their patient guidance, enthusiastic encouragement and useful critiques of this research work.

I would also like to extend my thanks to the technicians of the laboratory of the xxx department for their help in offering me the resources in running the program. Finally, I wish to thank my parents and brothers for their support and encouragement throughout my study.

Your Name

The Institute of Systems Engineering

YYYY/MM/DD



Resume

姓 名	王茗琛		入 學 時 間	2014.09
教育背景	起 止 年 月	就 讀 學 校	取 得 學 位 名 稱	
	2010.09–2014.06 2014.09–2017.06	XXX 大學 XXX 大學	XX 學士學位 XX 碩士學位	
在讀期間學術成果	發表的學術論文、著作（論文/著作名稱、報刊/出版社名稱、發表時間、刊物/出版社級別） 待寫, 待補			
	參加的學術項目（項目名稱、項目時間、立項單位、承擔的工作） 待寫, 待補			