出國報告（出國類別：其他：國際會議）

樓梯斜度與上/下樓梯步態的關聯性研究

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摘要

在本年度的 IIHMSP 2015 國際研討會中，本人參加了其中的一個與穿戴式運算和資訊安全之相關議程，進行口頭論文發表。在這個議程中，發表的論文所涵蓋的議題包括了數位浮水印、資訊隱藏、活動辨識、緊急通訊 APP 隨意網路建構等議題。而本人所發表的研究題目為“樓梯斜度與上/下樓梯步態的關聯性研究”，此研究議題是包含在運動辨識和環境訊息之情境運算的研究領域中。本研究的目標，是希望能提供在未來的生活環境中能夠建構出人類日常運動的情境感知之技術，透過此類技術，可以即時反饋人們利用爬樓梯所進行的健身運動、運動強度、以及運動的持續時間，以便能分析並了解人們的運動狀況，以及個體的身體健康狀況，可作為發展因應人口老化和提升健康條件的相關因應技術。

目次

一、目的

本次出國行程主要的目的是赴澳洲阿德雷德參加 IIHMSP 2015 國際研討會（第 11 屆智慧資訊隱藏與多媒體訊號處理國際研討會）進行論文發表，同行的還有另外 14 位外校的教授，包括有來自中興大學的教授一位、高雄大學的教授一位、朝陽科大的教授兩位、靜宜大學的教授一位、亞洲大學的教授一位、澎湖科大的教授兩位、南台科大的教授兩位、義守大學的教授一位、淡江大學的教授一位、長榮大學的教授一位、中州技術學院的教授一位等，各有不同的專業學術背景。在此次由前述各校教授互相邀請所共組的論文發表團體中，彼此之間於行程中之互相彼此照顧，另外又將各自於個人的最新學術研究成果彼此交流，相得益彰。

由於澳洲是一個很進步的國度，阿德雷德市則位於南澳洲，在澳洲的開發史上是相對較晚的地區，同團的教授們只有少數人曾到當地參訪過。對於我來說，到阿德雷德市的行程則是首次，因此抱著非常新鮮的心情赴會。

二、過程

本次出國赴赴澳洲阿德雷德參加 IIHMSP 2015 國際研討會的論文發表，研討會的舉辦地點是借用位在阿德雷德市的南澳州大學西市區校園內的會議廳所舉辦的，如圖一所示。在南澳州大學西市區校園內的會議廳會場，各項硬體的設備和設施外觀上看起來比較舊，需要特別的設定方能使用。在住宿方面，由於南澳州大學西市區校園在阿德雷德市區偏北的位置，屬於市中心商業區，旅館住宿費用較高，因此我們選擇市區偏南區住宿費較低的旅館居住。還好我們所居住的旅館附近有捷運，能直達到會場附近，使我們會議期間每天的交通都沒有問題。我們的論文發表團體是由各個學校的教授所組成，雖然大家參加的議程不同，但是在交通上的互相照應對彼此仍然很有幫助。

本次研討會之主辦單位是南澳州大學（University of South Australia），該校結合了 IEEE 協會訊號處理社群台南分會、哈爾濱工業大學、高雄應用科技大學、福建工程學院等單位之贊助，除了台灣的會議出席學者之外，大陸的學校單位亦有許多學者出席，使得此次會議嚴然成為兩岸會議但是在第三地舉辦。會場的活動如圖二所示，在圖二（a）中所示是會議報到處的入口迴廊，報到處除了有各國的參與人員外，還有一些當地大學的學生參加此盛會，在圖二（b）~（d）中，是會場內各個角落出

席學者之間聯絡交流的情況。

本次會議的第一場主題演講邀請了加拿大 Ryerson 大學的 Professor Ling Guan，演講題目是“Natural Human-Computer Interaction for the Creation of Lift-like Experience in the Immersive Environment”，中文翻譯是“針對在沉浸式環境中像順便搭載的體驗之創新的自然人機互動”，這項最新的研究指得是身臨其境之計算和通信是使用於信息和通信技術所生成之虛擬實境、混合實境和增強實境之環境，可執行使用者和沉浸式環境之間的人機互動。在身臨其境的環境中，可檢測、識別、處理、跟踪和視覺化物件和場景。以及在兩個或更多的沉浸式環境之間，交換和傳送信息。因為身臨其境之計算和通信是關於所有創造和交送生活之體驗，以身臨其境之計算和通信為中心，是我們如何以同樣的方式與身臨其境的環境自然互動，與之相同的情況等同於我們人類相互之間的互動，以及與周邊現實生活環境的互動，我們統稱之為自然人機互動。這個演講將首先提供了人機互動的身臨其境之計算和通信現狀的概述，以及自然人機互動帶來了的研究和我們日常生活令人興奮的進步。然後，演講繼續闡述近期的研究論文上的信息理論方法和工具，以及自然人機互動的發展研究，包括人的視覺、情感、手勢、動作、觸覺等，以及這些自然的方法互相融合，通過理論分析、圖例和創造生活的體驗。在演講的最後，Professor Ling Guan 致力於進一步說明自然人機互動技術的最終完善建議。

由於我的研究跟人機互動方面有些關聯，因此這個演講吸引了我的注意力，讓我投入了更多的興趣和注意力。本次研討會還有另外一場主題演講，邀請了中國電子科技大學的 Professor Ce Zhu，演講題目是“Visual Distortion Detection and Reduction in 3D Video”，中文翻譯是“在 3D 視頻中視訊變形檢測和視訊減降方法”，這項最新的研究跟我目前的研究較無關聯，因此我並未花太多的時間去聽演講。

在本次研討會中，本人發表的論文是有關於樓梯斜度與上、下樓梯時步態的關聯性研究，此研究是屬於利用穿戴式運算的相關技術之應用。對於如何取得上、下樓梯時的步態訊號，是與會研討的專家們有興趣並多有提問的問題，藉由本次研討會的機會，我也順帶地介紹了由本人所帶領的研發團隊所開發的最新穿戴式應用科技與實體應用系統之雛形，如圖三所示。本次參加 IIHMSP 2015 國際研討會的論文發表，所發表的研究主題是集中於此雛型系統在本次所發表的研究中，是穿戴在受試者的腳踝上方 3 公分處。此處是擷取步態訊號最明顯的位置，無論是平地或是樓梯，上樓或下樓的步態訊號，利用這個穿戴式系統，皆可以清楚地記錄到各個步態的動作。於論文的發表中，本人亦展示了此穿戴式裝置的實體雛型電路板零件（如圖四所示)，並引起現場參與研討人士的好奇眼光與詢問相關研發技術及動作辨識演

算法。

另外，現場的論文發表情形如圖四(a)和(b)所示，同時在同一論文發表場地，我參加了關於資訊隱藏運算與應用的主題研討，來增加個人的相關研究知識。我選擇參加了多媒體創新科技會議討論，其中有一篇是發表關於車輛導航駕駛警示系統研發的論文，是由高雄應用科大、澎湖科大及美國芝加哥州立大學的學者們共同發表的論文。這項研究中他們通過安裝車內 CCD 相機以捕捉圖像，並使用計算機視覺技術檢測夜間在車輛的前方車道和行車條件，開發了車道檢測駕駛員輔助系統，這個系統可以在低光照條件下提高駕駛的安全性。該系統的特點，還包括：車道探測、周圍車輛檢測、車道偏差檢測、以及距離估計等。在有大量汽車行駛的高速公路上檢測之後，該系統實際上已經達到理想的效果，且對相機圖像的處理速度可以達到每秒 20 幀，這幾乎可實現在高速公路上完成即時圖像處理的作業。

除了參加有關於嵌入式/穿戴式系統相關的應用科技之外，我還參加了音訊和語音訊號處理的會議。其中有一篇關於混合音樂信號的節奏變更技術的論文發表，這項研究是由日本仙台的 Tohoku 大學的團隊所進行的。我參加此論文發表的動機是，目前我正在研究人類在音樂環境中，對日常生活中各種身體活動的影響。該研究中提到，改變音樂訊號的速度是施加在音樂訊號處理的最基本訊號處理中的一種技術，傳統演算法（例如：相位聲碼器或時域諧波定標）能均勻地伸展和收縮輸入訊號。因此，這些方法不僅是改變了節奏，而且還改變了樂器聲訊號的結構，這等於是改變了樂器的音色。要改變音樂訊號的節奏，同時保持樂器的音色，這需要發展特殊的時間尺度非線性修正技術。為了實現這一技術，他們提出了音樂訊號的兩階段建模技術。聽了這位專家發表的講解之後，我對於改變音樂的節奏但是保持音樂的原音色有了更深入的認識，聽完此一論文發表深感收穫豐碩。

三、心得

本次出國參加 IIHMSP 2015 國際研討會的心得，可分成三個方面。第一方面心得，能夠與其他學校的教授共同生活在一起，在各自專業的領域產生了提升學術了解的相互交流。舉例來說，同團淡江大學的一位教授在與本人談到國內少子化議題時，分享了他任職的學校的策略與作法。因為他們學校是私立大學，對於未來少子化所帶來的生員銳減的問題非常敏感，因此早有一些因應策略，簡單的說就是先從差異化著手。他們先擬定招生策略，針對校外教學與國外交換學習綁在一起，設立了特別學程，該學程的要求是在該校讀三年課程同時加強英文訓練，接著必須無條

件地去澳洲姊妹校交換一年修完剩餘的課程。整個學程有完整的課程規劃，以及和澳洲姊妹校的配套課程與銜接。這個方案在該校大學招生時，已經形成了該校的一大特色，入學的同學不但高度認同該學程的宗旨，且家長的配合度有非常地高。簡單地歸納一下這個方案的特點，首先於入學前與招生簡章中已充分表明此學習方案的特色和相應的費用與補助，學生仍願意登記入學顯示出學生與其家長高度的認同感。其次，由於本方案須到澳洲姊妹大學交換，因為是英語環境與教學，因此需要配合加強語文訓練，這項措施引起學生與其家長高度的認同和配合，顯示出現代的學生和家長對於改變大學學習環境的渴望與利用移地情境學習的期待。再其次，由於此策略所衍生出的相關費用相當龐大，也確實有一些學生家庭在經濟上不能負擔，但是最終都能克服問題而完成移地交換學習的方案，也確實是一項奇蹟。這點充分說明了現代台灣家庭對於子女高端教育學習的重視態度。最後，這項策略的成敗系所與教師也必須承擔很大程度的責任，因為兩地教學習慣與文化差異，被交換的學生的學習效果，以及國外生活的人身安全等問題，往往超過事前的考量，因此也相當程度的增加了所有老師的負擔。

關於少子化的問題，另一位南台科大的老師也分享了他們學校的因應策略。根據他們學校管理高層的對國內現況的觀察，發現少子化海嘯來臨時無論公私立大學都將面臨不同程度的招生難題，公立末端的大學可能因為地點或設校時間較短，在知名度與教學特色上沒有明確的差異化特色，加上許多的私立大學或私立科大在學校特色與招生策略上仍未有成效，因此該老師表示南台科大校方認為降低學費與國立大學看齊，依該校的經營狀況仍然可以招收到足額的學生。從以上的交流，我充分可以看出，少子化危機是目前國內已無法避免的難題，但是各校仍有特出的因應策略，在此危機中可以看出老師與學校是一體的，需要老師與校方密切地配合，建立特色與發展策略，尋求從危機中脫身的道路。

第二方面心得，同行的興大教授分享了他的生活經驗，他說他還不到 60 歲但是沒有辦法爬樓梯，這讓我更進一步了解步態研究對健康促進的重要性，因此基於目前實驗室已有的研究成果，我與該教授分享了步態於健康效果的影響等知識，促使其想要實驗我所提供的建議。另外，也由於他的分享，讓我體驗到步態研究於病理分析上仍處於空百狀態的事實。這也引起我的研究興趣，算是此行的另外一項收穫。在參加研討會論文發表與交流方面，我聆聽了一位大陸學者發表的學術研究，對於中國近年來各方面的發展成果映象深刻。以我近幾年來與大陸學者交流的經驗來看，他們學術界的人士，我遇到的人是越來越年輕，學術研究成果也越來越先進，因此我感到我們台灣的相對優勢越來越不見了。

第三方面心得，到南澳洲區域參加研討會因為是第一次，因此特別注意當地的教育、發展與建設。在阿德雷德市至少有兩所高校，分別為南澳洲大學與阿德雷德大學。據導遊解說，南澳洲與澳洲其他地方不一樣，是由自由移民在上一世紀所開發的地區，因此當地充滿了歐洲的風情。由於澳洲地大人稀物產豐富，非常適合人居，與台灣人相比，澳洲人的生活就顯示出沒那麼有壓力。雖然如此，但是澳洲人也不為因此而滿足，在某些方面我發現澳洲人教育下一代非常用心。舉例來說，在一處公園綠地，當地政府邀請小學生在牆壁上作畫改善景觀，而作畫的主題是 50 年及 100 年後，當地的景觀想像圖。在參觀了哪些小學生的畫作之後，實在非常佩服當地人對當地永續發展的關心與培育下一代擄新視野之國民的做法。

四、 建議事項

澳洲的國土面積非常地大，是我們的很多倍，但是人口數卻與我們相當，且農業和礦業等物產豐富。目前澳洲經濟景氣隨著中國經濟發展放緩的影響，也受到一些影響，但是由於澳洲地大人稀，澳洲人的生活好像也沒有多大的影響。總體而言，澳洲的社會發展先進，教育事業也是相對地先進，尤其澳洲是英語系國家，目前社會上人力相對地也欠缺，是我們可以進行教育接軌的地區。如同前述的心得，澳洲是一個可以交換學生進行異地學習的地方，但是需要本校雲科大相關院系所的配合，仿照淡江大學的策略模式進行。本人將於適當時機，建議學校方面參考。

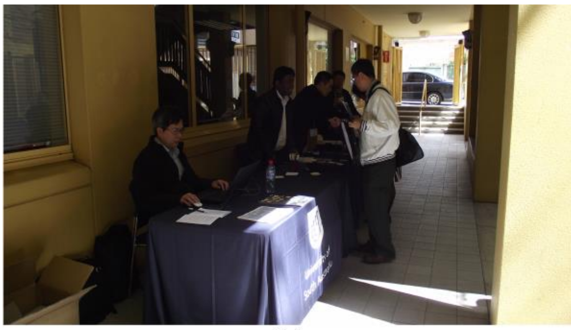
對於本次有這個機會，能夠赴南澳洲阿德雷德地區以參加國際研討會的方式，進入及拜訪這個地區，感到十二萬分的慶幸與珍惜。對於這樣的一個區域和參訪心得，本人當提醒本校領導高層應該重視與南澳洲相關教育單位之交流，對本校國際化和對未來發展播下成長的種子。未來本人對學生的教學上，也會盡力分享此次行程的所見所得，鼓勵年輕的一輩立足台灣、放眼天下，勇敢地追求個人的夢想實現。因此，本人建議以後有類似的研討會，政府應該站在鼓勵的立場，多多地贊助類似的出國活動，甚至是可以事先了解出國的教授群，予以分工組職期能發揮團隊的力量，影響國外相關學者的思考，有利於我國的對外學術交流管道拓展。

(a)

(b)

圖一：研討會的舉辦地點——南澳州大學（a）會場建築物前；（b）IIHMSP 2015 國際研討會會場前

(a)

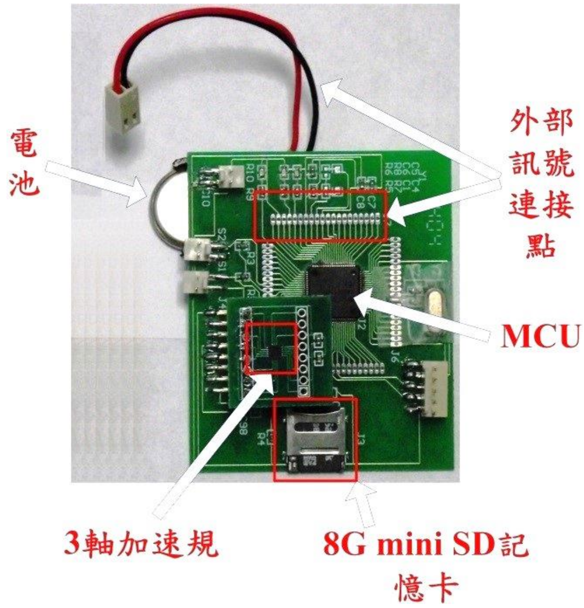


(b)

(c)

(d)

圖二：IIHMSP 2015 國際研討會會場之各項活動照片



圖三：穿戴式三軸加速度感測器雛型系統之設計

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圖四：研討會現場論文發表與研討情形

五、附錄

1. 攜回物品表

編號	名稱	內容
1	IIHMSP 2015 Conference Schedule	大會手冊
2	IIHMSP 2015 Conference Proceedings	大會論文集

2. 發表論文

Study on the Relationship between Stair's Slope and Upward/Downward Gaits in Stairs

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***Abstract*—In this study, we try to find a method to investigate the relationship between stair's slope and ascent/descent gaits in stairs. With the method, we can speculate the stair slope of a particular stair from a subject's gait so that we can use it to be an initial parameter for estimating the vertical distance the subject has climbed. In this way, this study could provide a practical method to realize the calorie consumption of daily life for persons who are intended to increase calorie consumption through climbing stairs. To speculate the stair slope of a particular stair, we need to collect, analyze, and compare signals from ascent/descent gaits on stairs with normal gaits from flat ground. In our investigation, we develop a novel device called activity monitoring unit (AMU), which is equipped with a tri-axial accelerometer and includes some signal analytical and processing schemes, to identify an estimated stair slope. To assure the effectiveness of our study, we recruit 50 subjects and select three stairs in our campus to conduct a few experiments. From the results of the experiments, the accuracy of our study reaches to 92.67% in the experiments.**

***Keywords*-gait analysis; legged locomotion; neural nets; acceleration measurement;**

I. Introduction

Human motion analysis is widely used in the research of human body structure [1], human motion tracking [2], gender identification [3], medical items [4], physical therapy [5], exercise training [6], etc. Gait recognition is a part of human motion analysis. Currently, gait recognition methods are generally divided into two categories. The first one is an image-based method [7][8], which could directly deal with image statistics. The other one is a model-based method [9][10], which could extract certain features from the model, and then analyze the alterations of the features. Most of the methods belong to the image-based method since it is relatively simpler and easier to process. However, we cannot directly obtain the exercise intensity of motion changes of gaits from this method.

As technology advances, the gait acquisition method is improved greatly as well. In the early stage, the gait information is obtained by taking and analyzing photos. In recent years, tri-axial acceleration sensors (or called accelerometers) are developed, which can record the track of human activity more effectively. In this way, the acquisition of gait signals becomes easier, simpler, and the cost lower. In [10], Muscillo et al. proposed a technique about adaptive Kalman-based Bayes estimation to classify locomotor activities in young and elderly adults through accelerometers. It is a pertinent research to our study. Although this study provided a good recognition rate, it focuses only on the classification of walking or climbing stairs. However, the study did not further discuss any other related investigation about the relationship between gait and the slope of stairs.

In the related research of human gait, there are no clues about the slope of stairs while climbing found in the literature. Furthermore, there is no easy and practical methods to realize calorie consumption for climbing stairs. In recent years, the research issues of health management and calorie consumption are popular. Therefore, our study try to provide an easy and practical method (*i.e.* only with employing accelerators) to realize the calorie consumption of daily life for persons who are intended to increase calorie consumption through climbing stairs. In this study, we developed a novel activity monitoring unit that uses an analytical scheme with support vector machine (SVM) clasifiers [11] for gait cycles to effectively identify the relationship between gait changes and the slope of stairs. The rest of this study is organized as follows. In Section II, we clearly describe the architecture of AMU. In Section III, we describe the stair slope recognization method and its process. In Section IV, we discuss the experimental results of our system. Finally, conclusions are made in Section V.

II. Materials

To obtain gait signals, we defined the measuring point in the side of the waist of a subject for signal measurement before preprocessing. Since it is close to the center of the body weight, it allows us to get more realistic gait signals and thereby improve comfort and convenience while measuring.

Before the feature extraction, we must first remove those useless signals as much as possible to get more effective features. In the stage of the signal analysis, it includes the

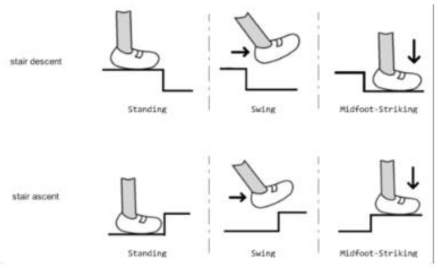


Figure 1. Three phases of a gait cycle.

Table I
THE GAIT FEATURES USED IN THE SVM CLASSIFIER FOR STAIR'S SLOPE.

Features	Description
$Mean_{AB}$	mean of the time interval of A to B.
$Mean_{AC}$	mean of the time interval of A to C.
$Mean_{AE}$	mean of the time interval of A to E.
$Mean_{CD}$	mean of the time interval of C to D.
$Mean_{CE}$	mean of the time interval of C to E.
$Mean_S$	mean of the sum of the peak and valley.
$Mean_P$	mean of the peak.
$Mean_V$	mean of the valley.
$Stdev_S$	standard deviation of the sum of the peak and valley.
$Stdev_P$	standard deviation of the peak.
$Stdev_V$	standard deviation of the valley.

steps of feature extraction and SVM training and classification. According to the concept of gait cycle (Figure 1), we extract stair ascent or descent gait signals and then import them into a SVM classifier, which is used for recognizing the slope of the stairs.

According to our experimental environment (*i.e.* stair ascent and descent), the gait cycle is divided into stance, swing, and midfoot-striking three phases as shown in Figure 1. To accurately identify the angle or slope of a stair, we need to find some useful gait features. Therefore, we conducted some experiments. From different angles of the stairs, we base on the concept of the gait cycle, and analyze the changes of gravity acceleration of the subjects during ascent and descent of a stair. Then we can obtain the relationship between the stair's angle and gait features. In Figure 2, the A, B, C, D, and E five points mark the feature points, which are used to represent the changes of gait signals. Among them, the point B in stair's descent and the point D in stair's ascent, both of them are a foot stable stance on a stair tread, and these points have a minimum value of gravity acceleration. Therefore, either stair's ascent or descent, in each midfoot-striking phase, the body will have a temporarily stable stance posture, but this time the state is quite similar to the stance phase.

According to Figure 2, we can find eleven features, which

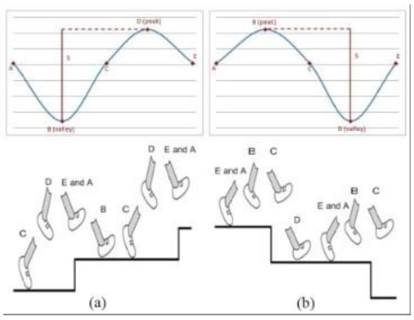


Figure 2. The referential diagram of the changes in gait and signal. (a) Stair ascent. (b) Stair descent.

are listed in Table I, related to time in the gait cycle for the classification of stair slope. By $Mean_{AB}$ and $Mean_{CD}$, we can use them to distinguish stair's ascent or descent. For $Mean_{AE}$, it can be used to correspond to the average width of each stair tread; and for $Mean_S$, it corresponds to the average height of each stair tread.

III. METHODS

In this section, we describe schemes in the phase of signal preprocessing and in the phase of gait feature extraction and signal classification by using SVM in the recognition of stair's slopes.

A. Signal Preprocessing

The signal preprocessing consists of noise reduction and signal reconstruction. In the noise reduction stage, to accurately identify the slope of stairs, we exclude the first phase of the gait cycle from the gait signals due to the starting unstable signals. Then, we use the second and third phases of the gait cycle as our references, which are required for the experiments.

In this study, we use discrete wavelet transform (DWT) to decompose the signals into frequency elements for eliminating the noise caused by body shaking, gait noises from walking postures and shoes, unstable walking speed of subjects, *etc.* The wavelet family adopted in this study is the sym7 of Symlets wavelet family [12]. The Symlets wavelet family is orthogonal and has better symmetry and minimal phase shift in comparison with other wavelet families. The denoised gait signals can be applied in the succeeding processing phase.

B. Signal Segmentation and Feature Extraction

We recruit fifty subjects and utilize three stairs with different angles. The subjects are asked to wear sensors in the side of the waist and walk at speed from 3 to 5 Km/hour

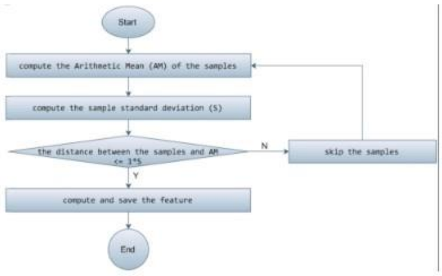


Figure 3. The workflow of the gait feature extraction.

(*i.e.* in the normal walking speed of common people) in different stairs. Then, we analyze the signals collected by AMU. To improve the recognition rate, we compute the gait features of Table I by the signal's samples scattered within a range of only one time of the sample's standard deviation. Figure 3 shows the detailed steps of extracting the gait features. First, we follow the concept of gait cycle and check the variability of the samples to find out the available ones. Finally, the eleven features (*i.e.* Table I) are calculated, and saved to the feature database until the follow-up gets SVM training.

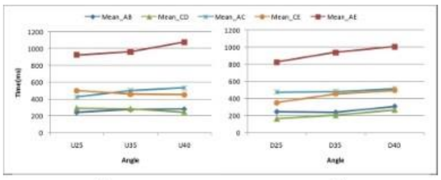
C. Signal Classification

The original problem is not conducive to calculate due to its high dimensions; and if we only use quadratic programming, it will become difficult to use the kernel functions to handle the inner product operation. Therefore, we use a radial basis function to transform the original problem into a dual problem in order to solve the original problem [11], and finally, we get the optimal boundary, which can distinguish each class. The most widely used kernel functions are defined as follows [13]. The gait features called $x = \{x_i\}, i = 1 \dots 11$, and the classification results called $y \in \{1, -1\}$.

$$k(x, y) = \exp\left(\frac{-||x-y||^2}{2\sigma}\right), \sigma \in \mathbf{R} - \{\mathbf{0}\} \tag{1}$$

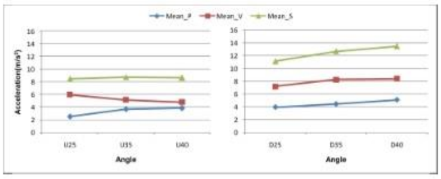
IV. Results

In this study, the experiments include fifty subjects, three different stairs, and a total amount of 300 times movements on the stairs. In the beginning of the experiments, the initial phase of all subjects is in the stance phase, and then the subject moves forward after stable stance. According to the number of stair treads, the subjects do a number of times of swing and midfoot-striking actions. At last, the subjects return to the stance phase, and complete one run of the experiments. For the same angle, each subject does one run of the experiments in stairs ascent and descent, respectively.



(a) (b)

Figure 4. The time distributions of different angles of stairs. (a) In stair ascent. (b) In stair descent.



(a) (b)

Figure 5. The acceleration distributions of different angles of stairs. (a) In stair ascent. (b) In stair descent.

According to the results of SVM training and classification, we use the *Precision* and *Recall* to express the classification accuracy, and the accuracy formulas are defined as below.

$$Precision = \frac{T_c}{T_c + T_f}, Recall = \frac{T_c}{T_c + F_c}. \tag{2}$$

In the formulas, T_c is the number of correct classifications, T_f the number of incorrect classifications, F_c the number of missing, and *Recall*.

We analyze the gait signals measured by 50 subjects in different angles on the stairs, and get the time and acceleration distributions of gait features as shown in Figures 4 and 5. From the figures, we clearly find out two phenomena. For example, the gait features $Mean_{CD}$, $Mean_{CE}$, and $Mean_V$ are inversely proportional to the angle in stair ascent but are proportional to the angle in stair descent. For the rest gait features, they are proportional to the angle in stair ascent and descent.

We use the RBF kernel for the SVM training and classification of stair slopes, and obtain the classification results, which are shown in Table II. In the table, the captical letters U and D indicate the actions of stair ascent and stair descent, and the number following the captical letters means the angle of the stairs. In each category of the table, the numbers indicate the classification number out of the fifty sets of samples. From the results shown in Table II, each category is given a good precision and recall except the angle of degrees 35 and 40.

Table II
THE CONFUSION MATRIX OF ALL TRAINING MODELS TO DO SVM PREDICTION.

Acctual	**Predicted**						**Recall**
	U25	U35	U40	D25	D35	D40	
U25	47	3	0	0	0	0	94.0%
U35	1	48	1	0	0	0	96.0%
U40	0	9	41	0	0	0	82.0%
D25	0	0	0	48	1	1	96.0%
D35	0	0	0	0	50	0	100.0%
D40	0	0	0	1	6	43	86.0%
Precision	97.9%	80.0%	97.6%	98.0%	87.7%	97.7%	

From the figures shown in Table II, the rates of *Precision* for U35 and D35 are lower, and the same situation happens to the rates of *Recall* for U40 and D40. The reason of lower *Precision* for U35 and D35 is due to a few samples from U40 and D40 classified to U35 and D35. Another reason could be the smaller difference between degrees 35 and 40. For the reason of lower *Recall* for U40 and D40, it is due to a few samples of U40 and D40 classified to U35 and D35. For the aforementioned classification misses, it might be guessed that some subjects would become more caution in climbing steep stairs. Therefore, they walk softer on steep stairs to avoid falls. Besides, since both of the gait features $Mean_{CE}$ in stairs ascent and $Mean_{AC}$ in stairs descent belong to the swing phase of a gait cycle. And, during this phase, gait signals are easy to be affected by other factors such as thinking, physical strength, and status of spirit. It is reasonable to speculate that recognition errors are most likely to cause.

V. CONCLUSIONS

In this study, we developed an AMU and its associted recognition schemes for the stair slope using upward/downward gaits on stairs. We gathered 300 sets of gait signals from 50 subjects with three different stairs. Then we selected the most representative features and entered them into the SVM classifier for training and stair slope classification. The accuracy of our study reached 92.67% in the experiments. This proved that we had selected the appropriate features for classification results.

In the future, we will continue research toward slopes, hoping to compute the height and length of stairs. Next, the observation from the *Precision* and *Recall* rates in the experiments reveal the insufficiency of the classifier. Better classification schemes should be investigated continuously. In addition, we hope to provide a practical way for people to understand how many calories they would consume, when they go hiking in the process of climbing slopes.

ACKNOWLEDGMENT

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