行政院國家科學委員會專題研究計畫 成果報告

以線掃瞄為基之光碟片自動光學檢測系統研究
研究成果報告(精簡版)

計 畫 類 別 ：個別型
計 畫 編 號 ：NSC 95-2221-E-216-025-
執 行 期 間 ：95 年 08 月 01 日至 96 年 07 月 31 日
執 行 單 位 ：中華大學機械工程學系

計畫主持人：邱奕契

計畫參與人員：碩士班研究生-兼任助理：高祥恩、賀孝簾

報 告 附 件 ：出席國際會議研究心得報告及發表論文

處 理 方 式 ：本計畫可公開查詢

中 華 民 國 96 年 08 月 24 日

行政院國家科學委員會補助專題研究計畫成果報告

※※※※※※※※※※※※※※※※※※※※※※※※※※
※　　　　　　　　　　　　　　　　　　　　　　　　※
※　　以線掃瞄為基之光碟片自動光學檢測系統研究　　※
※　　　　　　　　　　　　　　　　　　　　　　　　※
※※※※※※※※※※※※※※※※※※※※※※※※※※

計畫類別：☑個別型計畫　　□整合型計畫

計畫編號：NSC　95－2221－E－216－025－

執行期間：　　95 年 08 月 01 日至 96 年 07 月 31 日

計畫主持人：邱奕契　中華大學機械工程學系

計畫參與人員：蔡孟儒、李韋辰 中華大學機械與航太工程研究所

本成果報告包括以下應繳交之附件：

□赴國外出差或研習心得報告一份
□赴大陸地區出差或研習心得報告一份
☑出席國際學術會議心得報告及發表之論文各一份
□國際合作研究計畫國外研究報告書一份

執行單位：中華大學機械工程學系

中　華　民　國　96　年　08　月　20　日

行政院國家科學委員會專題研究計畫成果報告
以線掃瞄為基之光碟片自動光學檢測系統研究
The Study of a Linescan-based Automatic Optical Inspection System for Optical Discs

計 畫 編 號：NSC 95-2221-E-216-025
執 行 期 限：95 年 08 月 01 日至 96 年 07 月 31 日
主 持 人：邱奕契 中華大學機械工程學系
計畫參與人員：蔡孟儒、李韋辰 中華大學機械與航太工程研究所

一、中文摘要

光碟產業使用許多價格昂貴的自動光學檢測(Automatic Optical Inspection • AOI)設備以確保光碟品質，然而多數 AOI 設備都是仰賴進口。除此之外，並沒有任何一套設備可以將瑕疵品進一步做分級的工作。有鑑於此，本研究發展一套以線掃瞄取像技術為基礎之光碟片瑕疵偵測與分級系統，冀望能夠降低光碟製造業者購置 AOI 設備的成本，以提高產業的競爭力。

為了達成上述目標，本研究分兩階段進行。第一階段為硬體設備的規劃，其首要目標是將出現在光碟上的所有瑕疵完整且真實的呈現出來。本階段是本研究成敗的關鍵，因為如果影像中所出現的瑕疵失真或不完整，則後續的工作將變得毫無意義可言。儘管光碟片屬於高反射體，本研究採用亮場成像原理，同時擷取光碟片正反兩面的影像以節省時間。本研究所建構之硬體設備是由兩台線掃瞄攝影機、兩塊影像擷取卡、兩台線性光纖光源、一個步進馬達驅動之旋轉平台所組成。第二階段是利用影像濾波、梯度分析、影像分割、形態處理、物件分析、邊界偵測、及特徵抽取與分析等影像處理技術，發展一套瑕疵檢測程式，將瑕疵分割出來並予以分類。實驗顯示，本研究所發展之系統可成功檢查出光碟表面上的刮痕、流星、針孔、氣泡、條紋、及沾污等瑕疵。就 P4 3.0G 之個人電腦及 2048 pixels 解析度之線掃瞄攝影機而言，在 29 μm 及 117 μm 空間解析度下，檢測時間分別約需 0.765 秒及 0.172 秒。

關鍵詞：自動光學檢測、瑕疵偵測、分類、光碟片、亮場成像

Abstract

Optical disc industry uses many automatic optical inspection (AOI) systems to ensure their products defect-free. However, most of them are imported and expensive. Besides, none of them is capable of providing grading function for the defected discs. So the object of the research is to develop a flaw detection and classification system to reduce the cost for purchasing AOI equipment and increase the competitiveness.

To achieve the above-mentioned objectives, a two-step approach is adopted. The first step is to establish an apparatus to acquire images that will truly show all the defects on the surface of optical discs. This step is crucial to the success of the study, because if the captured defects are incomplete or camera cannot perceive defects at all, the developed system will be useless. Despite the high reflecting surface of the optical discs, we apply bright-field technique to capture images of both sides simultaneously to reduce inspection time. The developed imaging system consists of two line-scan cameras, two image grabbers, two line-type fiber-optic light sources, and a rotation stage driven by a stepping motor. The second step is to develop a flaw-detection program using image-processing techniques such as filtering, segmentation, blob analysis, edge detection, feature extraction and analysis, etc. to detect and classify defects. The experimental results show that the developed AOI system is successful in inspecting optical discs having specular surfaces for defects such as scratches, comets, pinholes, bubbles, streaks, etc. For a P4 3.0G PC with a 2048 pixels line-scan camera, if the desired spatial resolution is 29 μm, it takes 0.765 seconds to complete the inspection. If the desired resolution is 117 μm, it takes only 0.172 seconds.

Keywords: AOI, Flaw Detection, Classification, Optical Disc, Bright-field Imaging

二、緣由與目的

近年來我國在光碟片的生產上已躍居世界第一，在競爭激烈的環境中，如何使產品快速地大量的自動化生產，並且獲得良好的品質控管，將是能否提升競爭力的關鍵。產品的自動化檢測已是現今的趨勢，自動化檢測具有快速、穩定及高效率的優勢，而且能夠減少人工誤判或遺漏等缺失。目前國內光碟片自動化光學檢測的設備與技術大多倚靠國外廠商，由於價格昂貴，因此國內廠商必須支付龐大的費用來添購相關的檢測設備，導致成本大幅提高。再者，設備的維修與關鍵技術的取得都必須透過國外廠商，造成諸多不便。

有鑑於此，本研究採用機器視覺檢測的方法結合線掃瞄攝影機、亮場檢測、瑕疵偵測與瑕疵分類等技術，透過自動取像與分析的方式，建構一套光碟片自動光學檢測系統之雛型，可針對完成保護膠塗佈之光碟片進行線上檢測，自動地偵測出光碟片上的瑕疵並予以分類。瑕疵偵測的目的在於為產品的品質把關。瑕疵分類的目的則有二，其一為瑕疵產生源的追溯，其二為次級品的再分級。完成之系統可實際運用在光碟製造業上，以減輕業者購買 AOI 設備的成本，並提高國內光碟製造商的競爭力。

三、研究設備與方法

完成反射層濺鍍之光碟，其表面為鋁或金；完成保護層塗佈之光碟，其表面為亮光漆。無論是金屬或亮光漆都具有高反射率的特性，因此當光線照射在光碟表面時，很容易被反射回去。另一方面，射出成型後之基片或完成染料層塗佈之光碟皆屬透明材質。眾所周知，檢測透明材質與光亮材質必需採用不同的照明方式。透過實驗的方式，本研究採用特定的亮場照明（Bright Field Illumination）的檢測方式。此照明方式適用於完成染料塗佈及完成 bonding DVD 之檢測。

在取得理想之光碟影像後，接下來則運用影像處理與分析技術（影像濾波、影像分割、形態處理、物件搜尋、邊界偵測、特徵抽取），找出可能之瑕疵，最後再利用偵測所得之物件特徵（長短軸距離比、主軸方向、真圓度、灰階值、亮度對比、…等）形成所謂的特徵向量，透過分類技術（最短距離分類器、貝氏分類器、類神經網路分類器、或其他分類法則）將偵測所得之瑕疵分門別類。

為了能夠順利完成光碟片瑕疵偵測與分類，本研究將檢測系統分為硬體設備與檢測軟體兩個部份。前者之首要任務就是將出現在光碟上之瑕疵，真實完整的呈現在所取得的影像上。此部份是整個檢測系統成敗的關鍵，因為如果影像中所出現的瑕疵不完整，甚至攝影機根本看不到瑕疵，則後續的工作就變得毫無意義。瑕疵檢測軟體的工作則是將含有瑕疵之數位影像，透過影像處理技術將瑕疵分割出來並予以分類。

3.1. 檢測系統之硬體配置

本研究所自行設計與建構之光碟檢測機，主要之硬體設備包括線掃瞄攝影機（line-scan camera）、影像擷取卡、線型光纖光源、及旋轉機構。為了提高檢測速度，在線型光纖光源的照明下，使用兩台線掃瞄攝影機，對光碟片的正反兩面同步進行取像。各主要設備之規格與功能分述如下：

線掃瞄攝影機：本研究所使用之線掃瞄攝影機為美國 Dalsa 公司，型號 Spyder2 之線掃瞄攝影機，解析度為 2048 個像素，感測器之大小為 14 μm×14 μm。

影像擷取卡：除攝影機外，還需要影像擷取卡將攝影機所取得之資料轉換為電腦所能處理之影像，本研究所使用之影像擷取卡為 Matrox 公司的 Meteor II Camera Link 影像擷取卡。

線型光纖光源：為了讓攝影機掃瞄線所對應之條狀區域具有充分且均勻的照明，以便彰顯瑕疵，光源也相當重要。由於線掃瞄攝影機的特殊取像方式，取像時其視野為一條狀區域，因此傳統面掃瞄對整個面的打光方式並不適用。再者，為了連續地擷取影像，線掃瞄攝影機通常是以高於一般攝影機的取像頻率進行取像；換言之，其曝光時間較短，因此需要較強的光源才可以在瞬間提供足夠的光線。為了滿足上述取像方式之需求，本研究使用線型光纖導管（Morite MKG50x0.5W-1500S）搭配聚光鏡（MIL-50）及鹵素燈（Hayashi

LA-150UE）進行照明。

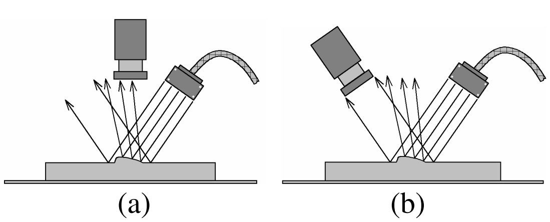
此外，本研究特別將攝影機放置在三軸平移台上，以方便使用者手動進行攝影機位置的微調。平移台之精度為 10μm，可微調之範圍為 25 *mm*。

3.2 照明方式

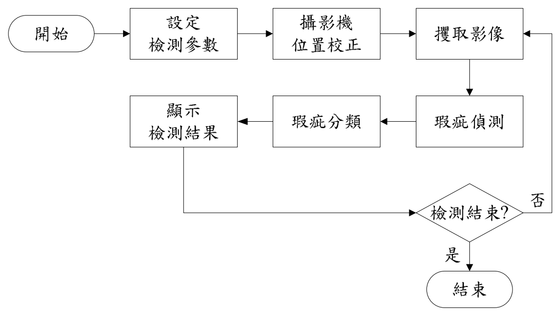
根據光源、攝影機及待檢測物之相對位置、以及所獲得影像為暗或亮，檢測方式可分為亮場檢測(Bright Field Inspection)與暗場檢測（Dark Field Inspection）兩大類。請參考圖一(a)，暗場檢測是利用光線反射的原理，當入射光照射在光碟片表面時，由於光碟片具有高反射率的特性，光線會依入射角度產生反射。如果反射光線無法進入鏡頭，則攝影機所取得之影像將呈現全黑的狀態，因此稱為暗場。然而當入射光照射到瑕疵時，由於瑕疵具有不平整的表面，將迫使光線反射路徑改變，導致部份反射光進入攝影機鏡頭，因此在暗影像中所呈現的亮點即為瑕疵。一般而言，暗場檢測適用於高反射物體之檢測。

請參考圖一(b)，亮場檢測是入射光照射在光碟片之表面，經反射後如果反射光直接進入攝影機之鏡頭，使得感知器接收最大的光線，因此影像將呈現全白的狀態，因此稱為亮場。當入射光照射到瑕疵時，反射角度將偏離正常路徑，使得反射光線無法順利進入攝影機之鏡頭，造成瑕疵於影像中呈現暗點。一般而言，亮場檢測適用於透明物體之檢測。

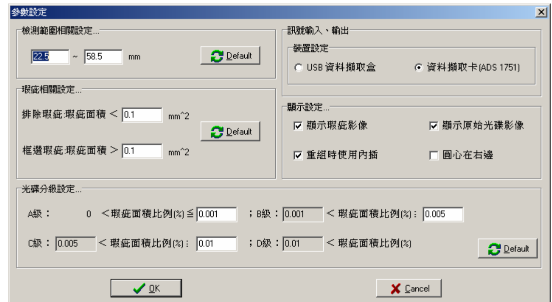
前段製程之檢測物為透明體，因此對於瑕疵的檢測方式應採用亮場檢測。反之，後段製程之檢測物為具有高反射率之非透明體，瑕疵檢測方式理應採用暗場檢測。然而實驗結果顯示，對於光碟表面瑕疵之檢測，無論是前段製程或是後段製程，使用亮場檢測都可獲得不錯的效果。



圖一、亮場及暗場檢測之差別：(a) 暗場檢測示意圖；(b) 亮場檢測示意圖。



圖二、光碟表面瑕疵檢測流程圖。



圖三、參數設定對話框。

3.3 瑕疵檢測方法與流程

光碟表面瑕疵檢測流程如圖二所示，包含檢測參數設定、影像擷取、瑕疵檢測、瑕疵分類及檢測結果顯示等五個步驟。第一步是參數設定，有鑑於客戶對品質之要求有所不同，廠商對於瑕疵品的判斷標準也不盡相同，因此有必要提供一個方便的使用者介面，讓使用者可根據客戶的要求調整瑕疵檢測參數。其次對攝影機位置進行校正，以確定取像區域正確。完成上述兩個步驟後即可開始進行檢測。檢測時首先透過 RS232 通訊介面，控制旋轉機構轉動光碟，搭配線掃瞄攝影機擷取待測光碟影像。完成取像，接著選擇適當的演算法，對待測影像進行瑕疵的偵測。偵測出瑕疵後，接下來便是將瑕疵分類。瑕疵分類的目的在於追溯瑕疵產生的源頭，以了解那個製程出了問題。除此之外，也可根據瑕疵的類型，將有問題的光碟進行再分級。

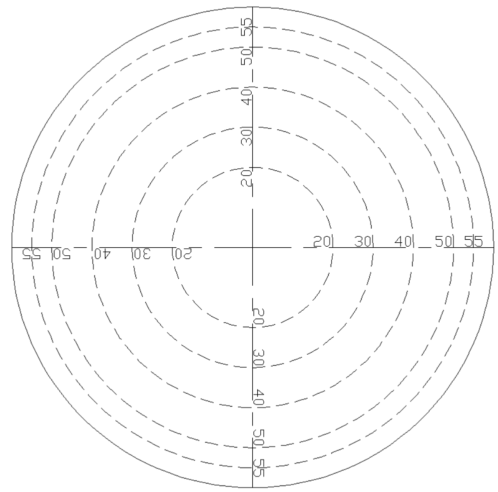
3.3.1 參數設定與位置校正

檢測前必須對檢測系統進行參數設定及攝影機位置的校正。有些廠商只針對資料讀取區進行檢測，忽略其他不影響資料存取穩定性之印刷區，因此檢測前須先進行相關參數設定，若檢測參數有所變更時，操作人員可由圖三所示之參數設定對話框輸入檢測範圍。程式中預設之檢測範

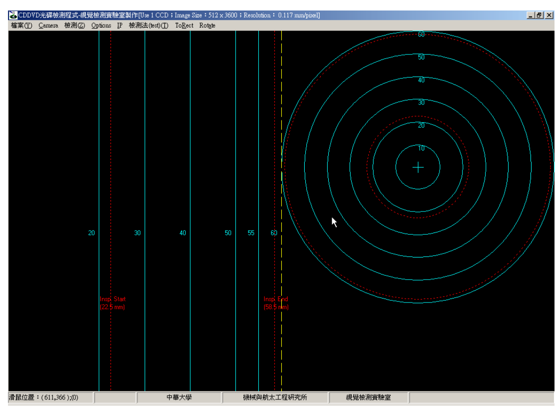
圍為半徑 22.5 *mm* -58.5 *mm* 之環狀區（光學讀寫頭讀取之範圍）。可供修改之參數除檢測範圍外，還包括程式介面及檢視相關設定。對於光碟分級的相關設定也可於此視窗中設定，可依不同的需求，設定不同的分級標準，將光碟分為 A、B、C、及 D 四個等級。程式介面方面，使用者可於視窗選單中，選擇是否繪製虛擬尺規及檢測範圍。由於經由線掃瞄取得之光碟原始影像為長條型影像，此功能的目的就是在長條影像中繪製相對應的尺規及檢測範圍，以方便使用者進行後續之攝影機位置校正時，檢視取得之光碟影像是否符合需求。當瑕疵之面積過小，不至於構成瑕疵要件時，使用者可以選擇不顯示小瑕疵，以避免畫面出現過多瑕疵反而忽視了重要的資訊。因此「排除瑕疵」輸入欄，即是因應此一需求而設計的，當影像中物體的面積大於此設定值時，才會被判定成瑕疵。當符合條件之瑕疵過多時，也許只框出其中幾個面積較大之瑕疵即可，此時使用者可以透過「框選瑕疵」欄輸入代表面積的數值，當瑕疵面積大於此設定值時才會被框選出來。

完成參數設定後，接下來是進行攝影機位置的校正。如果攝影機的光學軸沒有對準，所取得之影像將出現偏移的現象。因此本研究在影像擷取前，先以自製之校正片（圖四）進行攝影機位置的校正，以確保攝影機取得正確的影像。如圖四所示，校正片上繪製半徑分別為 20、30、40、50 及 55 *mm* 的五個圓，作為校正用之參考尺規。校正時，校正程式會依據所選用的影像解析度，在螢幕上繪製與校正片上相對應的五個圓（圖五右以 20、30、40、50 及 55 標示的五個同心圓）。再者，因為線掃瞄攝影機擷取所得之影像屬於長條型影像，因此我們進一步將校正片影像中的五個圓展開成如圖五左所示的五條直線（圖五左以 20、30、40、50 及 55 標示的五條平行線）。圖中以青色實線繪製之直線與圓是根據影像解析度繪製出的虛擬尺規；而以紅色虛線繪製之直線與圓則是使用者可自行設定之檢測範圍（在圖三「檢測範圍相關設定」中進行變更）。

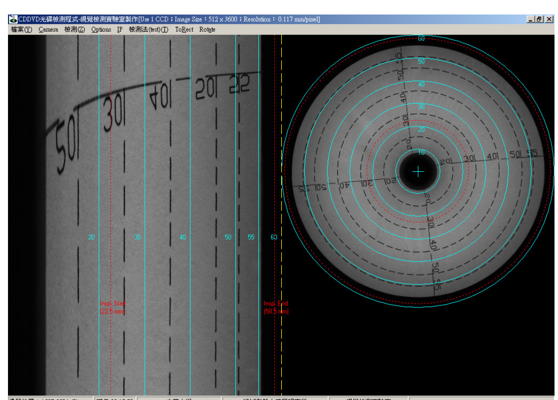
這些參考用之虛擬尺規，讓使用者可以很容易的確認所取得之影像是否正確。圖六與圖七分別代表攝影機位置錯誤及正確時校正片取像之結果及畫面顯示之情形。透過此校正程式，使用者可快速及正確的完成攝影機系統的校正工作。



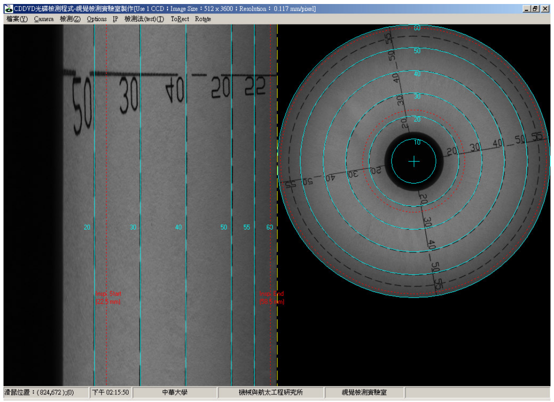
圖四、校正片示意圖。



圖五、虛擬尺規。



圖六、校正片上之圓與直線（黑色虛線）與系統繪製之圓形及直線尺規（青色實線）沒有重合，可見攝影機之位置不正確。



圖七、當校正片上之圓與直線(黑色虛線)與系統繪製之圓形及直線尺規(青色實線)重合時，代表攝影機位置之校正已完成。

3.3.2 瑕疵偵測

瑕疵偵測的目的是要找出影像中可能是瑕疵的區域。如前所述，本研究所採用之亮場照明方式是將線型光源傾斜一個角度，因此攝影機視野內的每一個點所接收之光線並不相同。導致擷取所得之影像，即使是同一列(row)上的點也會有不同的灰階值。此現象使得傳統以面為基礎或一個區域使用一個閥值的影像分割方式，並不適合用來分割線掃瞄影像。

線掃瞄影像上同一列的每一個像素點雖然會有照明不均的現象，但是同一行(column)上的每一個像素點所接受到的光線理論上應該是相同的。本研究就是根據此一原理，發展以閥值線為基礎的四種瑕疵偵測法，包括①平均灰階值瑕疵檢測法、②灰階標準差瑕疵檢測法、③平均梯度瑕疵檢測法、以及④多閥值瑕疵檢測法。這四種方法都是以影像中的行為處理單元，為每一行設定一個閥值，構成所謂的閥值線（Threshold line）。再以此閥值線對線掃瞄影像逐列進行分割，以達到瑕疵偵測的目的。從文獻可知[1-2]，灰階標準差法是上述四種方法中最適合者。因此，以下僅就這個演算法做介紹。

一般說來，灰階異常的像素點就是瑕疵點。所謂的“灰階異常”，指的是其灰階值與正常灰階值的差異超出某個事先設定的門檻值。但是，如何界定灰階值是否正常？根據統計學上對標準差的研究發現，若實驗數據屬於常態分佈（亦即屬於高斯分佈），則大約會有 68%以上的數據與該組數據的平均值的差距會在一個標準差以內。因此，如果影像中灰階異常的區域（瑕疵），在影像中屬於少數（32%以下），則可藉由灰階標準差的計算，得到大部分灰階正常像素與平均值的差異。換言之，當灰階值與平均灰階值的差在一個標準差以內者，可視為正常；反之，則視為異常。

灰階標準差法首先根據統計學上標準差的觀念，設定上控制線及下控制線。接下來，將各像素的偏差值（deviation）與灰階標準差（standard deviation）做比較，以判定各像素之灰階值是否正常。令 f 代表待測影像，以灰階標準差法檢測時首先利用(1)及(2)式計算各行的灰階平均值及灰階標準差。例如，$Avg(x)$及 $\sigma(x)$分別代表第 x 行的平均灰階值及灰階標準差；接著利用(3)及(4)式建構上下控制線（閥值線）；最後再將影像中的每一個點代入(5)式即可將影像分割。

$$Avg(x)=\frac{1}{H}\sum_{y=1}^{H}f(x,y) \quad ;for\ x=1,W \qquad (1)$$

$$\sigma(x)=\sqrt{\frac{\sum_{y=0}^{H-1}\left(f(x,y)-Avg(x)\right)^2}{H}} \qquad (2)$$

$$T_{up}(x)=Avg(x)+\sigma(x)+T_\sigma \qquad (3)$$

$$T_{dw}(x)=Avg(x)-\sigma(x)-T_\sigma \qquad (4)$$

$$I_R(x,y)=\begin{cases}0; & if\ T_{dw}(x)>f(x,y)<T_{up}(x)\\ 255; & otherwise\end{cases} \qquad (5)$$

其中 H 為影像的高度，T_σ 為閥值（預設值為 5）。經過上述處理所得到之影像 I_R 為黑白影像，其中黑色（灰階值 0）代表背景；白色（灰階值 255）則代表異常之像素。

3.3.3 瑕疵分類與光碟分級

在光碟的生產過程中，每道製程所可能產生的瑕疵不同，因此若能將檢測出的瑕疵分類，則可得知那個製程發生問題以及出現甚麼問題。除此之外，根據瑕疵的類別、數量及出現之位置，也可以進一步將被判定為瑕疵品的光碟分級出售。

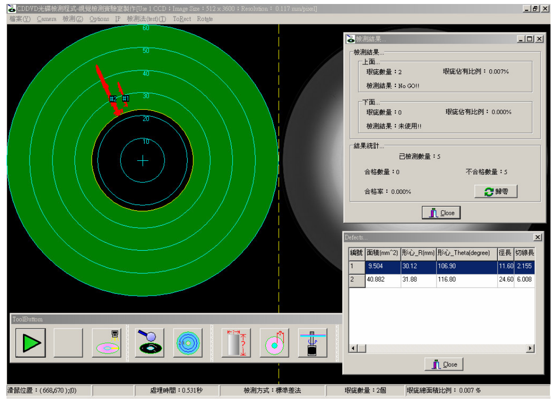
經由瑕疵偵測後，可能是瑕疵的區域已被偵測出，接下來便是將瑕疵做進一步的分類。瑕疵分類的方法，主要是依據瑕疵的幾何特徵、分佈位置及灰階特性來進

行。瑕疵分類的前置作業是特徵抽取，將有利於分類的特徵從瑕疵中抽取出來。本研究所使用之特徵包括面積、徑向長度、切線方向長度、真圓度、及長短距離比。其次根據瑕疵的特徵，透過分類法則將瑕疵分類。常見的分類法包括分類樹、支援向量機、及類神經網路等。為了讓使用者容易了解分類法則，本研究採用分類樹進行分類。各種特徵之定義以及如何根據瑕疵之特徵進行分類之研究不勝枚舉，礙於篇幅在此不予贅述，有興趣之讀者請參考文獻[3-9]。

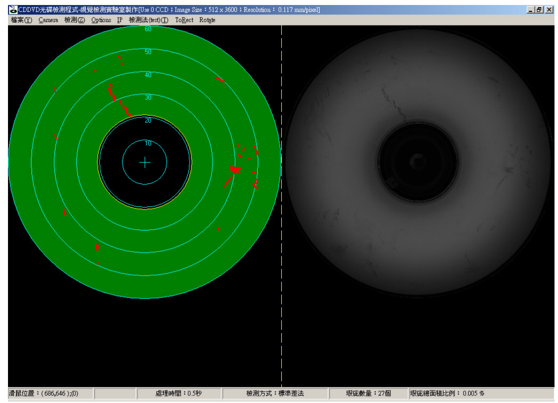
四、研究結果與討論

本研究的目的之一是提供一種擷取光碟片表面影像之設備與方法。針對此一目的，本研究建構完成一套如圖八所示之檢測硬體系統。此系統利用旋轉機構讓光碟片旋轉，並在光碟片旋轉的同時，利用上下兩台線掃瞄攝影機對光碟片之正反兩面進行取像。使用線掃瞄攝影機取像的好處是可以避開光碟片的反光效應。本研究的另一個目的是發展一套瑕疵檢測系統，此軟體程式可針對擷取所得之光碟片上下兩面影像進行即時的檢測。圖九所示為發展完成之瑕疵檢測程式畫面，程式中顯示原始光碟影像以及偵測所得之瑕疵影像、瑕疵數量及各瑕疵之詳細資料，包括面積、徑向長度、切線方向長度等。「檢測結果」對話框中將顯示光碟的檢測結果及品質等級。「結果統計」中則顯示已檢測光碟之總數及合格率。此外，使用者可依需求進行攝影機參數、顯示相關、檢測範圍、瑕疵定義及分級等相關設定。

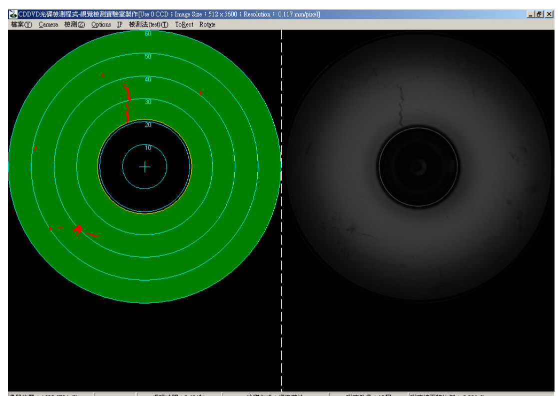
圖八、光碟表面瑕疵檢測機。



圖九、光碟表面瑕疵檢測程式介面。



圖十、完成染料塗佈製程 DVD 樣本對染料塗佈面之取像及檢測結果：右圖為原始光碟影像；左圖為檢測結果，其中以紅色標示之區域為檢測出之瑕疵。



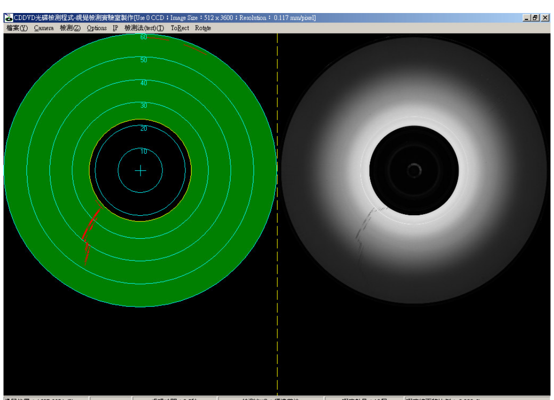
圖十一、完成染料塗佈製程 DVD 樣本對資料面取像及檢測之結果：右圖為原始光碟影像；左圖為檢測結果，其中以紅色標示之區域為檢測出之瑕疵。

4.1. 瑕疵檢測結果

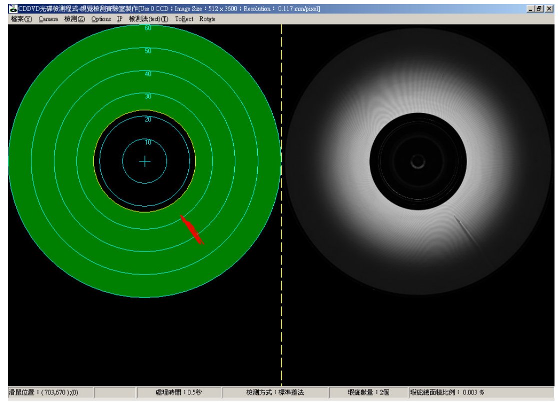
本研究所發展之光碟表面瑕疵檢測系統，對於完成染料塗佈或已完成 Bonding 之 DVD 都有不錯的取像及瑕疵檢測結

果。首先就完成染料塗佈製程之 DVD 樣本進行取像及檢測說明。此類樣本屬於完成第二製程之 DVD，其結構僅包括透明基片與染料層。一般說來，出現在此類樣本的瑕疵包括染料塗佈異常及基片表面刮傷等表面瑕疵。此類樣本屬於半透明物，瑕疵可能出現在光碟片的正面或反面。為了探討那一面比較容易檢測出瑕疵，本研究針對染料面及資料讀取面進行檢測。結果顯示，並非對任意一面取像都能擷取到所有的瑕疵。例如，當瑕疵出現在染料面，則必需對染料面取像才能看得到瑕疵；反之，如果瑕疵出現在資料讀取面，則必需對資料面取像才能看到瑕疵。圖十及圖十一所示為對染料面及資料面進行取像及檢測之結果，右圖為重組後之原始光碟影像，左圖為瑕疵檢測之結果，其中以紅色標示者為檢測出之瑕疵。

對於完成 Bonding 之 DVD 樣本，由於已完成染料塗佈、反射層濺鍍、保護膠塗佈及 Bonding 等程序，樣本中可能出現各式瑕疵，而且表面具有高度反射性。針對此類樣本，本研究是以亮場照明的方式取像。實驗結果顯示，無論是染料異常或刮傷，在亮場照明下均無所遁形。然而，由於此類樣本具有多層次的結構（各層具有不同的特性），因此擷取所得之影像中有些會出現波型紋路。圖十二及圖十三所示為取像及檢測之結果，右圖為重組後之原始光碟影像，左圖為瑕疵檢測之結果，其中以紅色標示者為檢測出之瑕疵。



圖十二、完成 Bonding DVD 樣本之取像及檢測結果：右圖為重組後之原始光碟影像；左圖為檢測結果，以紅色標示者為檢測出之瑕疵。



圖十三、完成 Bonding DVD 樣本之取像及檢測結果：右圖為重組後之原始光碟影像；左圖為檢測結果，以紅色標示者為檢測出之瑕疵。

4.2 討論

在影像解析度方面，受限於現有之線掃瞄攝影機其最高解析度為 2048 pixels，因而最高解析度僅可達 29 *μm/pixel*。若要擷取更細微的瑕疵影像，則必需採用更高解析度的攝影機。在瑕疵偵測方面，為了解決影像在水平方向照明不均的問題，本研究提出四種以閥值線為基礎之瑕疵偵測法，包括平均灰階法、灰階標準差法、平均梯度法及多閥值法。經過幾項指標的評估後，本研究採用灰階標準差法，此方法適用於檢測完成染料塗佈之半透明膠片及完成 Bonding 之 DVD 樣本。

在瑕疵完整性方面，對於完成染料塗佈之半透明樣本而言，瑕疵可能同時顯現在染料面及資料面上。實驗顯示，有些瑕疵從資料面取像所得到的瑕疵較完整。對完成 Bonding 之樣本而言，刮傷與染料異常等瑕疵均可順利的被檢測出來，然而有些影像內會出現如圖十三右所示之波紋。這些波紋利用瑕疵偵測法處理後在瑕疵影像中會以雜訊般的小點出現。由於本研究在後續之影像處理過程中，會再利用尺寸濾波（size filtering）將面積太小的瑕疵移除，因此並不會影響檢測結果。

本研究所使用之「灰階標準差瑕疵檢測法」是建構在瑕疵數量少於 1/3 的基礎上。因此當具有瑕疵之像素點過多時，有些瑕疵是會被忽略的（仔細觀察瑕疵檢測結果即可發現此一問題），換言之，本研究所使用之演算法仍有許多改善的空間。

除此之外，縮短檢測時間或提高瑕疵解析能力，也是值得努力的地方。

五、結論

取像結果之良窳是決定機器視覺檢測結果成功與否的關鍵。本研究採用線掃瞄攝影機搭配旋轉機構，並以亮場照明的方式取像，可成功擷取光碟片影像。取像時可依需求變更掃描線之解析度（包括 2048、1024 及 512 三種），其相對應之空間解析度分別為 29 μm、58 μm 及 117 μm，取像時間約為 0.2 秒。檢測時間與影像大小有關，檢測一張 2048×3600 之影像約需 0.765 秒；1024×3600 之影像約需 0.359 秒；512×3600 之影像則只需 0.172 秒。總結來說，本研究之主要貢獻包括：

- 提供一種針對高反射性光碟片表面打光之亮場照明方法。此方法是讓線型光源與光碟面成一角度，並以非均勻的方式打光。以此方法取得之影像，在水平方向會有不均勻的情形，搭配以閥值線為基礎之瑕疵偵測法可將瑕疵分割出來。
- 提供一種校正光碟片表面瑕疵檢測系統之方法及其系統。此方法利用自製之校正片及自行開發之校正軟體程式，可讓系統之校正更加方便與迅速。
- 提供一種光碟片表面瑕疵檢測方法。本方法根據線掃瞄攝影機取像原理，所發展之「灰階標準差瑕疵檢測法」，可避免取像時光線不均的影響。

六、成果自評

本研究在提案時所預期完成之工作項目及具體成果包括：

1. **光碟自動光學檢測系統**：發展一套以線掃瞄攝影機與旋轉機台為基礎之自動光學取像系統。預期之取像速度必需小於 0.8 秒。
   針對這個工作項目，本研究所研發之檢測機台，其取像速度約為 0.2 秒，遠快於預期之目標。
2. **瑕疵偵測**：發展一種適合線上即時檢測之高速瑕疵偵測法，以便將光碟上所有的瑕疵完整的呈現出來。
   針對這個工作項目，本研究如預期的完成適合線上即時檢測之「灰階標準差瑕疵檢測法」。此演算法在瑕疵為少數的前題下，能夠將大部份的瑕疵找出來。
3. **瑕疵分類**：將瑕疵區分為流星、刮傷、污點、凹陷、針孔、灰塵、氣泡等類別。
   由於樣本的取得不是很容易，而且樣本屬於一次樣本（離開潔淨室即受污染），使得檢測實驗不易進行。再者，樣本中並未包含所有類型的瑕疵，因此本研究只能針對現有之光碟及瑕疵進行測試。因此，對於這個工作項目，我們僅能根據瑕疵的大小、主軸方向為徑向或切線方向粗略的將瑕疵區分為污點、染料塗佈異常、流星或刮傷。
4. **檢測速度**：檢測時間希望能夠控制在 1 秒內，否則本系統將不具競爭力。
   本研究檢測一張 2048×3600 之影像也只需要 0.765 秒，因此順利達成目標。
5. **次級品之再分類**：將檢測出瑕疵之光碟片分成 A, B, C, D, E 五個等級。
   本研究並未將瑕疵品再分級，這是因為瑕疵分類並未達到預期的目標。隨著 DVD 光碟片價格的驟降，是否有必要增加此一功能，頗值得進一步探討。

七、參考文獻

[1] 蔡孟儒，”光碟片表面瑕疵檢測系統之研發”，碩士論文，中華大學機械與航太工程研究所，2006。

[2] 邱奕契、蔡孟儒， “線掃瞄影像瑕疵偵測法之比較,”第十四屆全國自動化科技研討會，J17-J22，2006 年 6 月，苗栗，臺灣。

[3] 林憲忠，“積層陶瓷電容瑕疵檢測與分類”，碩士論文，中華大學機械與航太工程研究所，2004。

[4] G. Wang and T.W. Liao, “Automatic Identification of Different Types of Welding Defects in Radiographic Images,” NDT and E International, Vol. 35, No. 8, pp. 519-528, 2002.

[5] M.R. Driels and D.J. Nolan, “Automatic Defect Classification of Printed Wiring Board Solder Joints,” IEEE transactions on components, hybrids, and manufacturing technology, Vol. 13, No. 2, pp. 331-340, 1990.

[6] C.J. Du and D.W. Sun, “Pizza Sauce Spread Classification Using Colour Vision and

Support Vector Machines," Journal of Food Engineering, Vol. 66, No. 2, pp. 137-145, 2005.

[7] X. Zhang, C. Krewet, and B. Kuhlenkotter, "Automatic Classification of Defects on the Product Surface in Grinding and Polishing," International Journal of Machine Tools and Manufacture, Vol. 46, No. 1, pp. 59-69, 2006.

[8] 莊富傑，"導線架瑕疵之偵測與分類使用類神經網路"，碩士論文，中華大學機械與航太工程研究所，1999。

[9] 陳冠宇，"紋理分析在彩色影像分類上之應用"，碩士論文，中華大學機械與航太工程研究所，2002。

出席國際學術會議心得報告

計畫編號	NSC 95-2221-E-216-025
計畫名稱	以線掃瞄為基之光碟片自動光學檢測系統研究
出國人員姓名 服務機關及職稱	邱 奕 契 中華大學機械系
會議時間地點	自 96 年 06 月 26 日至 96 年 06 月 29 日; 日本\關西\京都大學
會議名稱	IEA/AIE 2007: The 20th International Conference on Industrial, Engineering & Other Applications of Applied Intelligent Systems
發表論文題目	**Selecting an Appropriate Segmentation Method Automatically Using ANN Classifier**

一、參加會議經過

IEA/AIE 2007 是應用人工智慧領域專家學者年度重要聚會之一，會議時間從六月二十六日起至六月二十九日止，共四天。本人於台北時間六月二十五日清晨八點半從桃園國際機場搭乘長榮 BR2132 班機出發，於日本當地時間十二點左右抵達關西機場。大會共安排了兩場 Keynote Speeches：二十六日早上的專題演講題目為『Towards New Content Services by Fusion of Web and Broadcasting Contents』，演講者為京都大學 Katsumi Tanaka 教授。二十七日早上之第二場專題演講講題目為『Pattern Discovery from Graph-Structured Data – A Data Mining Perspective 』，演講者為 Hiroshi Motoda 教授。

本次 IEA/AIE 會議共收到 462 篇稿件，採用 116 篇，錄取率為 25.11%。會議分成 regular paper, short paper, 及 poster 三大類。此次論文的發表，多數是以口頭方式發表，以 poster 發表者只有 10 篇。本人被安排在六月二十六日下午"Vision II" 場次報告，本場次共有三篇文章發表，本人最後報告，報告時間從十四點五十分至十五點十五分，報告二十分鐘，接受發問五分鐘。

二、與會心得

專題演講之內容令人相當感興趣，內容是有關整合電視內容與網頁內容之最新進展。此最新技術的目的是要讓人們在看電視的同時也能夠利用電視瀏覽網頁；反之，在瀏覽網頁的同時也能夠利用電腦看電視。當使用者在觀賞電視新聞時，網頁上會自動將新聞之標題及重點內容顯現出來，在此同時系統會自動搜尋與新聞標題相關之網頁內容。例如，當新聞內容提到”金閣寺”，網頁搜尋引擎會自動將在有關金閣寺之網站或新聞搜尋出來，因此使用者有需要進一步了解金閣寺之歷史或相關事件，即可立即點閱。此方式的好處是免除同時使用電腦及電視的麻煩。

本人在發表結束後，被與會專家提問相當多問題，每一個問題都相當深入，提供之意見也頗值得參考。其中有些問題是本人從未曾思考過的問題，透過此次的提問，讓我有機會深入思考，同時也啟發我進一步研究的方向。

Selecting an Appropriate Segmentation Method Automatically Using ANN Classifier

Yih-Chih Chiou and Meng-Ru Tsai

Institute of Mechanical and Aerospace Engineering, Chung Hua University,
Hsinchu, Taiwan, 30012, R.O.C.
chiou@chu.edu.tw

Abstract. In general, we can easily determine the manufacturing step that does not function properly by referring to the flaw type. However, a successful segmentation of flaws is the prerequisite for the success of the subsequent flaw classification. It is worth noticing that, different segmentation methods are needed for different types of images. In the study, a mechanism that is capable of choosing a proper segmentation method automatically has been proposed. The mechanism employed artificial neural networks to select a suitable segmentation method from three methods, i.e., Otsu, HV standard deviation, and Gradient Otsu. The selection is based on the four features extracted from an image including standard deviation of background image, variance coefficient, the ratio of the width to height of both foreground and background histograms. The results show the success of the proposed mechanism. The high segmentation rate reflects the fact that the four carefully selected features are adequate.

Keywords: Segmentation, Feature Extraction, Flaw Detection, Flaw Classification, BPN Network.

1 Introduction

Flaw detection is an important procedure in the quality assurance of products. In general, by referring to the defect type, we can easily determine the manufacturing step that does not function properly. Hence, the ultimate goal of flaw classification is to identify each flaw type such that the sources of flaws can be identified and the manufacturing parameters can be adjusted accordingly. However, a successful segmentation is the prerequisite for the success of the subsequent flaw detection and classification. Segmentation is a process to separate desired flaws from background. Thresholding is the most commonly used flaw detection method [1], [2], [3], [4], [5]. Several researchers [3], [6], [7], [8], [9] have suggested the use of image gradient to detect flaws. On the other hand, a number of authors have applied standard deviation [9], [10], [11] to discover flaws. It is worth noting that most segmentation methods are sensitive to noise, illumination variance, object shape and size, grayscale variance of foreground and background, etc. In addition, different types of flaws need different segmentation methods.

H.G. Okuno and M. Ali (Eds.): IEA/AIE 2007, LNAI 4570, pp. 195–206, 2007.

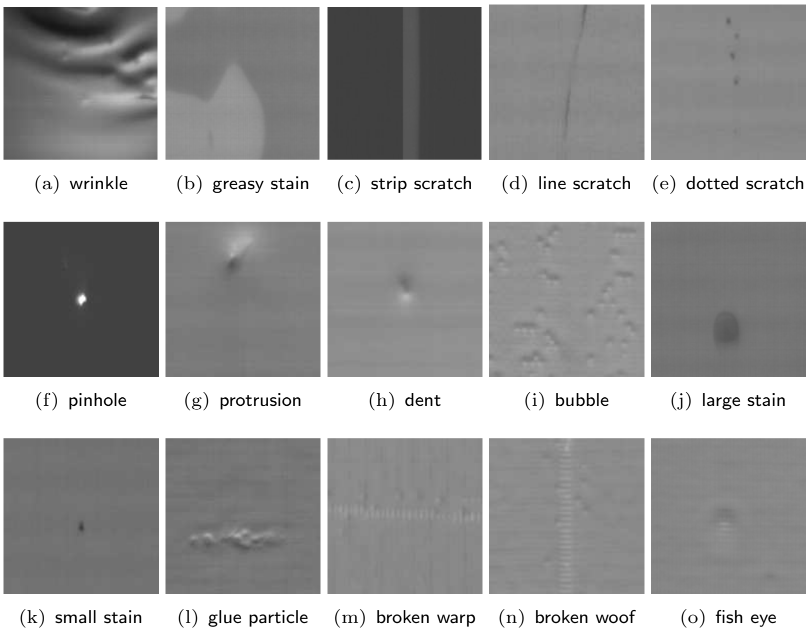


Fig. 1. Sample images of the fifteen types of flaws

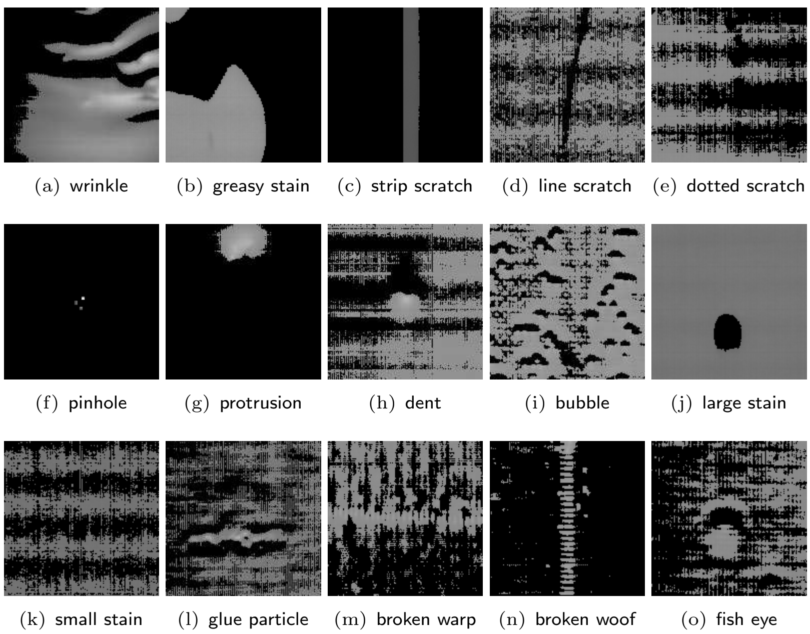
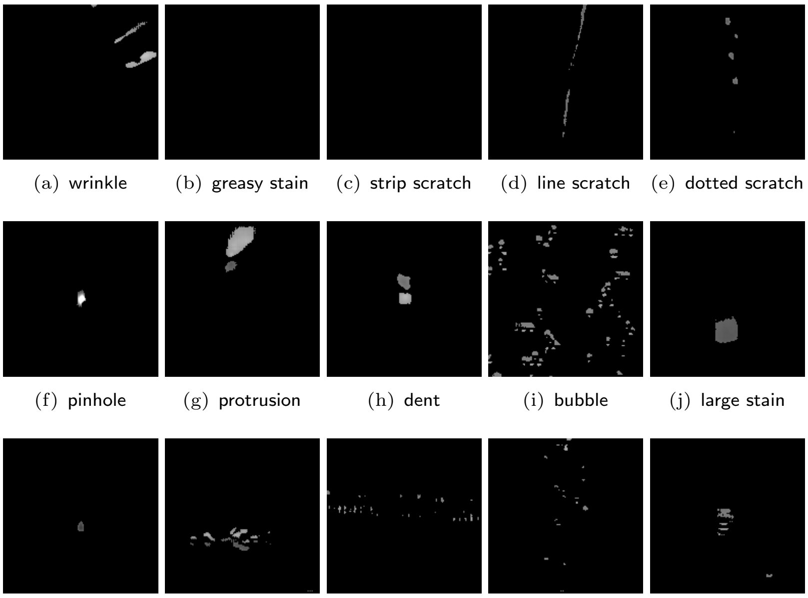


Fig. 2. Segmentation results of the fifteen types of flaws as shown in Fig. 1 using Otsu's method. It is evident that Otsu method is good for wrinkles, greasy stains, strip scratches, and large stain, but it is not suitable for segmenting other flaw types.

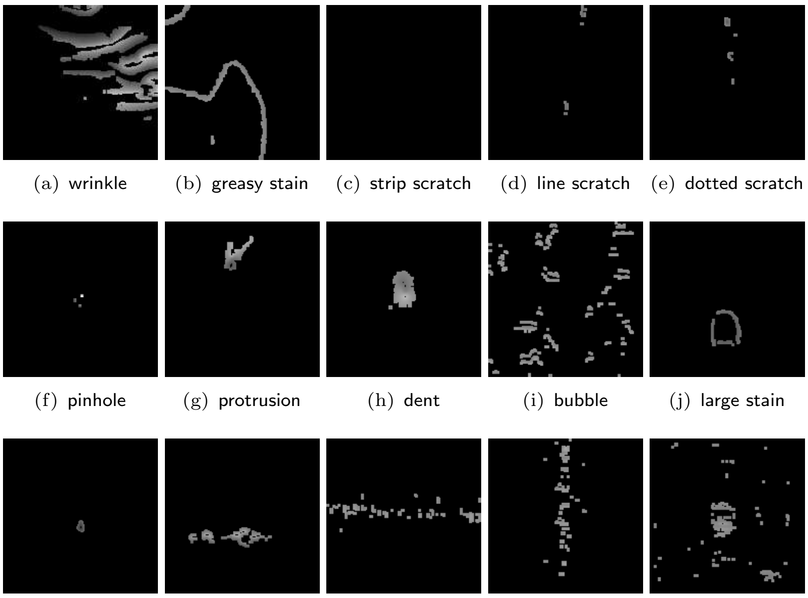


(a) wrinkle (b) greasy stain (c) strip scratch (d) line scratch (e) dotted scratch

(f) pinhole (g) protrusion (h) dent (i) bubble (j) large stain

(k) small stain (l) glue particle (m) broken warp (n) broken woof (o) fish eye

Fig. 3. Segmentation results of the fifteen types of flaws as shown in Fig. 1 using HVStd method. It is evident that HVStd is good for some flaw types, but quite bad for others.



(a) wrinkle (b) greasy stain (c) strip scratch (d) line scratch (e) dotted scratch

(f) pinhole (g) protrusion (h) dent (i) bubble (j) large stain

(k) small stain (l) glue particle (m) broken warp (n) broken woof (o) fish eye

Fig. 4. Segmentation results using GradOtsu method. It is clear the method is suitable for segmenting wrinkle and small defects. For large defects, only their profiles are shown.

Figure 1 shows 15 types of flaws to be segmented and classified. As shown since these images were collected at different time and from different production lines of paper and plastics manufacturing industries, they differ greatly; some are brighter, some are darker, and some have textured background. Besides, flaws differ greatly in size, shape, and quantity. Strictly speaking, satisfactory results are unobtainable if one segmentation method is applied to all types of images. For example, Fig. 2 shows the segmentation results using Otsu's method [12]. It is apparent that some results are good while others are unacceptable. Similar results (Figs. 3 and 4) were observed when Horizontal and Vertical Standard Deviation (HVStd) method or Gradient Otsu method (GradOtsu) were applied. The two segmentation methods developed in the research will be described in detail in Sect. 2.2. The results suggest that if an inadequate method is applied, the desired flaws might not even present in the result image. As a result, misclassification of flaws occurs. In other words, attempting to use one single segmentation method to process all types of flaws is impractical. In view of that, the object of the study was to develop a mechanism that is capable of selecting a suitable segmentation method automatically.

2 Methodology Overview

It is evident that it is not possible to obtain acceptable results for all types of images by using one particular segmentation method. A better approach would be to select an appropriate segmentation method for each image type. Nevertheless, the selection should be automatic. Thus, it is desirable to develop a mechanism that is capable of selecting an appropriate segmentation method automatically. In the study, 1697 sample images of size 152×152 were used. All samples contain at least one flaw. To achieve the aforementioned objective, each sample was segmented using Otsu, HVStd, and GradOtsu sequentially. Then, by visual inspection of the three segmentation results, each sample was assigned to one of the three groups according to which method derived the best segmentation result. It is worth noting that for some samples two methods derived equally well segmentation results. If this is the case, we randomly assigned them to either group. Nevertheless, the random assignment might affect the final segmentation rate.

The proposed mechanism starts with the segmentation of the input image using HVStd method. The segmentation results in two images, i.e., flaw image and background image. A flaw image is referred to as the image containing only pixels that are regarded as abnormal while a background image is referred to as the image containing pixels other than abnormal pixels. The next step is to extract features from the images. As to which feature is useful in discriminating one group from another, we used the extracted features to construct scatter diagrams. By examining the distributions of the three groups, whether a feature is suitable for classification was learned. After that, an artificial neural network using backpropagation learning algorithm [13] (hereafter we called the kind of network BPN network) was established. Finally, a segmentation method chosen by the BPN network was used to segment the input image so as to discover flaws.

2.1 Segmentation Methods

In this study, three segmentation methods, including Otsu, HVStd, and GradOtsu, were used to segment images. Aside from Otsu method, the other two methods are described in detail as follows:

(1) HVStd: The method first calculates grayscale means and standard deviations for each row and column and then uses the derived information to generate a threshold value for segmentation. Let I_O be an original image, $I_O(i,j)$ be the grayscale value of the pixel located at column i and row j. The grayscale mean for each column and row are given by

$$\mu_{col}(i) = \frac{1}{H}\sum_{j=0}^{H} I_O(i,j);\ for\ i = 1, W \tag{1}$$

$$\mu_{row}(j) = \frac{1}{W}\sum_{i=0}^{W} I_O(i,j);\ for\ j = 1, H \tag{2}$$

where W and H are the width and height of the image. After that, (3) and (4) are used to calculate standard deviations for each column $\sigma_{col}(i)$ and each row $\sigma_{row}(j)$.

$$\sigma_{col}(i) = \sqrt{\frac{1}{H}\sum_{j=0}^{H} (I_O(i,j) - \mu_{col}(i))\quad};\ for\ i = 1, W \tag{3}$$

$$\sigma_{row}(j) = \sqrt{\frac{1}{W}\sum_{i=0}^{W} (I_O(i,j) - \mu_{row}(j));}\ for\ j = 1, H \tag{4}$$

Let δ_{row} and δ_{col} be deviations of rows and columns, respectively. We have

$$\delta_{col}(i,j) = |I_o(i,j) - \mu_{col}(i)|\ ;\ for\ i = 1, W \tag{5}$$

$$\delta_{row}(i,j) = |I_o(i,j) - \mu_{row}(j)|\ ;\ for\ j = 1, H. \tag{6}$$

Finally, we can use the following equation to derive the resulting image, I_R.

$$I_R(i,j) = \begin{cases} I_O(i,j),\ if\ |\delta_{col}(i,j) - \sigma_{col}(i)| > T_{std}\ and \\ \qquad |\delta_{row}(i,j) - \sigma_{row}(j)| > T_{std} \\ \qquad 0,\ otherwise \end{cases}. \tag{7}$$

The pre-selected value T_{std}, is determined to be 5.0 after a rigorous test of images at hand.

(2) GradOtsu: Different from Otsu's method, which segment an image directly, the method first calculate the image's gradient and then uses Otsu's method to segment the gradient image in order to reveal flaws. The method was developed specifically for extracting defects from wrinkles corrugated type surfaces. First of all, we use Sobel's edge detector to derive each point's gradient and generate

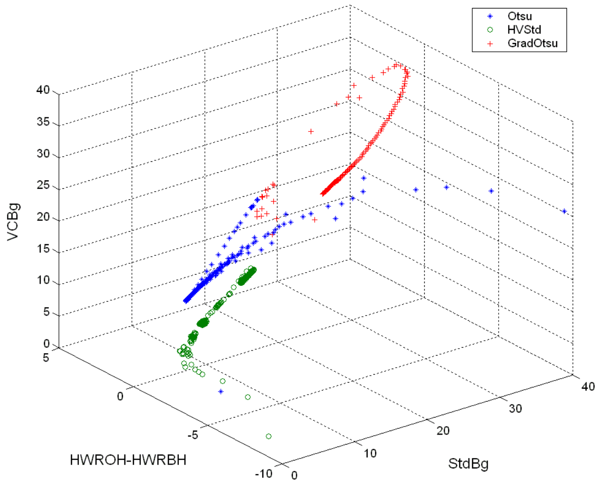


Fig. 5. Scatter diagram of the three segmentation methods. It is clear that the three groups of images are well separated.

a gradient image I_G. In general, pixels with high gradient can be regarded as defects. Therefore, gradient image, I_G, is segmented subsequently using Otsu's method to obtain a binary image, I_B. After segmented using Otsu, the resulting binary image, I_B, denotes a defect map of the input image.

2.2 Features for Network Training

To enable the proposed mechanism to select a suitable segmentation method automatically, we need to realize that why one segmentation method produces better result than that produced by others. Hence, we extracted several features from images. After a rigorously check, we decided to use the following four features, i.e., standard deviation of background (StdBg), variance coefficient of background (VCBg), the ratio of height to width of the histogram of the original image (HWROH), and the ratio of height to width of the histogram of the background image (HWRBH). The reasons for choosing the four features are due to their ability to distinguish one image group from another. Referring to the scatter diagram shown in Fig. 5, the three groups are well separated if the four features are used to construct the plot. Definitions of the four features are depicted as follows.

(1) StdBg: StdBg is the abbreviation of Standard Deviation of Background image. Standard deviation is commonly used in statistics to measure how spread out the values in a data set is. *StdBg* is defined as

$$StdBg = \sqrt{\frac{\sum\sum(f_{bg}(i,j) - \mu_{bg})^2}{N_{bg}}}, \tag{8}$$

where $f_{bg}(i, j)$ denotes the grey level of the pixel located at column i and row j of the background image, μ_{bg} is the grayscale mean of the background image, $N_{bg}$is the count of background pixels. Here, *StdBg* was used primarily to check the uniformity of the background image. If grayscale values of the background pixels are all close to their grayscale mean, then the standard deviation is low.

(2) VCBg: In a statistical sense, variance coefficient is defined as the ratio of standard deviation to grayscale mean. Since background image was used to calculate grayscale mean, μ_{bg}, and standard deviation, σ_{bg}, we called the ratio of σ_{bg} to μ_{bg} variance coefficient of background ($VCBg$), i.e.

$$VCBg = \sigma_{bg}/\mu_{bg}. \tag{9}$$

Statistically speaking $VCBg$ can be used to evaluate the degree of dispersion of background pixels' grayscales, too. The larger the number is, the more dispersed the grayscale values are.

(3) HWROH: The ratio of height to width of the histogram of the original image ($HWROH$) is another useful feature. We defined HWROH as

$$HWROH = \frac{H_{raw}/N_{raw}}{W_{raw}/256}, \tag{10}$$

where H_{raw} and W_{raw} are the height and width of the histogram of the original image, respectively, N_{raw} is the count of the pixels in the image. The height of a histogram is defined as the count of the bin with the maximum count of pixels. As to the width of a histogram, it is defined as the difference between the largest bin number and the smallest bin number with non-zero count. This feature is useful in measuring how complex an image is. In general, the larger the number is; the narrower the grayscale spreads. A small value of HWROH usually implies that there are several objects in the image.

(4) HWRBH: The ratio of height to width of the histogram of the background image ($HWRBH$) is a useful feature, too. We defined HWRBH as

$$HWRBH = \frac{H_{bg}/N_{bg}}{W_{bg}/256}, \tag{11}$$

where H_{bg} and W_{bg} are the height and width of the background histogram, respectively, N_{bg} is the count of the background pixels. We can obtain H_{bg} and W_{bg} in a similar manner. $HWRBH$ is useful in knowing the grayscale distribution of background pixels. The higher the value is, the narrower the grayscale spreads.

2.3 Flaw Segmentation Using BPN Networks

Unlike classification tree or other statistical methods, neural network approaches do not require exact knowledge of the statistical distribution of input items. A BPN network is the most popular among all the known ANNs. Hence, we employ

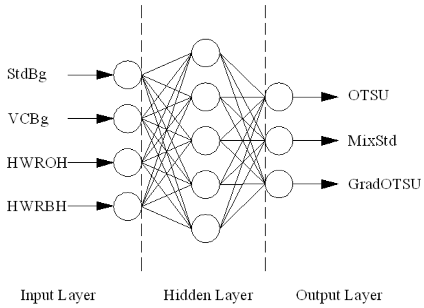


Fig. 6. The 4×5×3 network structure for selecting a segmentation method

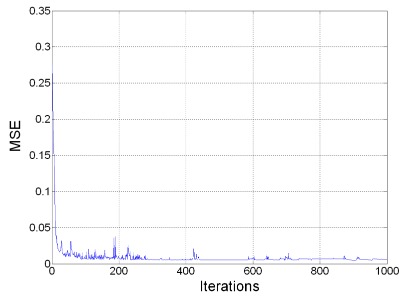


Fig. 7. The plot of mean squared errors vs. iterations (η=0.25; MSE=0.01)

a BPN network to select an appropriate segmentation method. Let T_i and O_i be the i^{th} desired and actual outputs, respectively, then the Mean Squared Error (MSE) between them can be determined by

$$MSE = \frac{1}{2}\sum_{i=1}^{n}(O_i - T_i)^2. \tag{12}$$

The back-propagation network uses the gradient steepest decent method to iteratively adjust the connection weights between two consecutive layers so as to minimize MSE between the actual output and the desired output. For example, the adjustment of the weights connecting the last hidden layer j and the output layer k is done as follow:

$$W^o_{jk} = W^o_{jk} + \eta\delta^o_k H_j, \tag{13}$$

where η is known as the learning rate, δ^o_krefers to the error signal at each node of the output layer k, and H_j refers to the output signal at each node of the hidden layer j. The adjustment is repeated until the MSE drops below a prespecified value. In general, if the samples contained in the training set are the representatives of the objects to be recognized later the classification results should be satisfactory.

As can be seen from Fig. 5, the three groups of images clustered at different locations. In view of that, a simple network structure can be expected. Figure 6 shows the ANN network for selecting a proper segmentation method. The input layer consists of four units, i.e., the four features extracted from the image to be classified, including *StdBg*, *VCBg*, *HWROH*, and *HWRBH.* The output layer consists of three units, i.e., the three segmentation methods to choose from, i.e., Otsu, HVStd, and GradOtsu. Before a BPN network can be effectively used to classify, it must be trained with sufficient number of samples. The samples are randomly divided into two sets. The training and testing sets consist of 929 and 768 samples, respectively. We first used the images in the training set to train the network. As shown in Fig. 7, the training using back-propagation algorithm converges quickly. The recall process shows that only 4 samples were misclassified, i.e., the recall rate is 99.57%. To explore the ability of the trained network, we presented each sample in the testing set to the network one-by-one. At the recognition stage, the network is fed with the four features extracted from the inputted image and a proper method is chosen. The recognition rate is 99.61%. The high recall and recognition rates strongly imply that the selected features are extremely appropriate for discriminating one class of image from another.

3 Results and Discussions

For comparison, the same 15 images, as shown in Fig. 1, were segmented using the proposed mechanism and the results were shown in Fig. 8. In contrast with the segmentation results shown in Figs. 2-4, the results are satisfactory. The outcomes suggest that the proposed method perform well in selecting a suitable segmentation method automatically. In addition, the results indicate that the four carefully selected features, i.e. StdBg, VCBg, HWROH, and HWRBH, proved to be well suited for discriminate one group from another. To explore the capability of the proposed mechanism further, the images in the testing set were segmented and classified. The experimental results are listed in Table 1. With regard to the classification of the 15 types of flaws, we made use of BPN

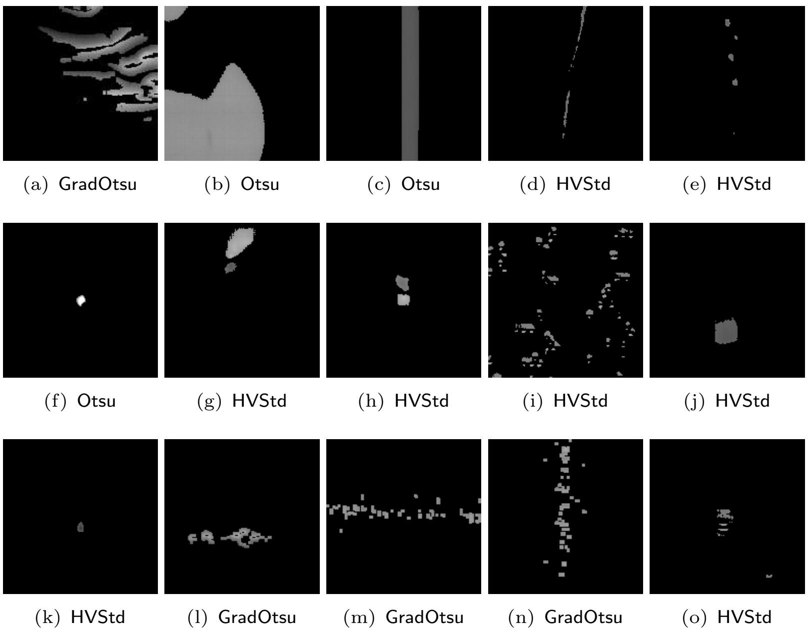


Fig. 8. Segmentation results of the 15 images shown in Fig. 1 using the proposed methodology. The method below each image indicates the method automatically selected.

network, too. The five-layer 10×10×15×10×15 network for flaw classification is composed of an input layer, three hidden layers, and one output layer. The input layer consists of 10 units, i.e., the 10 features extracted from the image to be classified. The output layer consists of 15 units, i.e., the 15 types of flaws to be categorized. The classification rate is 97.66%. Detailed classification results are listed in Table 1.

In the course of the experiment, we found that the sample images could be classified into three categories, i.e., images with point/line flaws, images with smooth surface, and images with corrugated surfaces, according to the types of flaws. The finding is important because the decision of which segmentation method should be used is closely related to this. In other words, although the selection of segmentation methods is done automatically, some facts can be observed as followings:

- HVStd is the most frequently selected method. It is suitable for segmenting images with point/line flaws, such as small stains and dotted scratches.
- GradOtsu is suitable for segmenting images with corrugated surfaces, such as wrinkles.
- Otsu method is most suitable for segmenting images with smooth surfaces, such as greasy stains, strip scratches, and large stains.
- For some types of flaws, different segmentation methods might derive similar well results. For examples, either HVStd or GradOtsu can be used to segment bubbles and small stains.

Table 1. Flaw detection and classification results of the samples in test set

Flaw Type	Samples	Misclass. samples	Classification Rate (%)	Method Chosen	Run-Time (ms)
Wrinkle	77	0	100.00	GradOtsu	34.1
Strip Scratch	12	1	91.67	Otsu	29.2
Greasy Stain	17	1	94.12	Otsu	45.5
Line Scratch	4	1	85.71	HVStd	24.6
Protrusion	7	1	85.71	HVStd	40.1
Dent	91	0	100.00	HVStd	17.3
Pinhole	5	0	100.00	Otsu	26.0
Large Stain	52	0	100.00	HVStd	18.9
Small Stain	160	3	98.12	HVStd	17.2
Dotted Scratch	16	3	81.25	HVStd	22.7
Bubbles	102	2	98.04	HVStd	18.3
Glue Particles	137	2	98.54	GradOtsu	31.9
Fish Eye	34	0	100.00	HVStd	31.1
Broken Warp	12	2	83.33	GradOtsu	29.9
Broken Woof	42	3	92.86	GradOtsu	31.3
Total	768	18	97.66		

Execution time is an important issue, too. HVStd is the default method for segmenting an incoming image; therefore, if it is selected for the subsequence segmentation, the image has no need to be segmented again. On the other hand, if other methods are chosen, the image will be re-segmented. Therefore, the run time depends on the segmentation method chosen. Besides, the run time is related to the flaw types. The average run time evaluated by a 1200MHz personal computer can be seen in Table 1.

4 Conclusion

In this paper, we have proposed a novel methodology for segmenting a variety of images. The main advantage of the proposed thresholding scheme is its ability to choose an appropriate method from the three segmentation methods automatically. The proposed method does not require establishing complicated classification tree; we use ANN classifiers for both image segmentation and flaw classification, instead. The automatic selection is according to the features extracted from the image to be segmented. The overall segmentation and classification rates of the 768 images in the test set are 99.69% and 97.66%, respectively. The experimental results show the effectiveness of the selected features for classification and the power of BPN networks.

Acknowledgements. This work was supported by National Science Council (NSC), Taiwan, R.O.C., under Grant No. 95-2622-E-216-009-CC3.

References

1. Ng, H.F.: Automatic Thresholding for Defect Detection. In: Proc. 3rd Int. Conf. Image and Graphics, pp. 532–535 (2004)
2. Yeh, C., Perng, D.B.: A Reference Standard of Defect Compensation for Leather Transactions. The Int. J. of Advanced Manufacturing Technology 25(11-12), 1197–1204 (2005)
3. Mery, D., Carrasco, M.: Automated Multiple View Inspection Based on Uncalibrated Image Sequences. In: Kalviainen, H., Parkkinen, J., Kaarna, A. (eds.) SCIA 2005. LNCS, vol. 3540, pp. 1238–1247. Springer, Heidelberg (2005)
4. Cheriet, M., Said, J.N., Suen, C.Y.: A Recursive Thresholding Technique for Image Segmentation. IEEE Trans. Image Processing 7(6), 918–921 (1998)
5. Chan, F.H.Y., Lam, F.K., Hui, Z.: Adaptive Thresholding by Variational Method. IEEE Trans. Image Processing 7(3), 468–473 (1998)
6. Mery, D.: Crossing Line Profile: A New Approach to Detecting Defects in Aluminum Die Castings. In: Bigun, J., Gustavsson, T. (eds.) SCIA 2003. LNCS, vol. 2749, pp. 725–732. Springer, Heidelberg (2003)
7. Gao, H., Siu, W.C., Hou, C.H.: Improved Techniques for Automatic Image Segmentation. IEEE Trans. Circuits Syst. Video Technol. 11(12), 1273–1280 (2001)
8. Tancharoen, D., Jitapunkul, S., Chompun, S.: Spatial Segmentation based on Modified Morphological Tools. In: Proc. Int. Conf. Information Technology: Coding and Computing, pp. 478–482 (2001)

9. Bellon, O.R.P., Silva, L.: New Improvements to Range Image Segmentation by Edge Detection. IEEE Signal Processing Lett. 9(2), 43–45 (2002)
10. Stojanovic, R., Mitropulos, P., Koulamas, C., Karayiannis, Y., Koubias, S., Papadopoulos, G.: Real-time Vision-based System for Textile Fabric Inspection. Real-Time Imaging. 7(6), 507–518 (2001)
11. Sauvola, J., Pietikainen, M.: Adaptive Document Image Binarization. Pattern Recognition 33, 225–236 (1999)
12. Otsu, N.: Threshold Selection Method from Gray-Level Histograms. IEEE Trans. Syst. Man, Cybern. SMC-9(1), 62–66 (1979)
13. Freeman, J.A., Skapura, D.M.: Neural Networks Algorithms, Applications and Programming Techniques, 1st edn. pp. 89–128. Addison-Wesley, London (1991)