MELON AUTHENTICATION BY AGRI-BIOMETRICS

Identifying Individual Fruits using a Single Image of Rind Pattern

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Abstract: We propose a new method of biometric authentication, called agri-biometrics that identifies an individual fruit using a single image of its rind patterns. Our proposed method normalizes the rotations in depth of the fruit and extracts a set of image features, which are compatible to the 'minutiae', from the normalized image; thus, it enables us to apply a state-of-the-art technique of fingerprint matching to identify the rind patterns of fruit. We conducted large-scale experiments to identify/verify 1,776 individual melons in practical situations where the images were taken under different pose and illumination conditions on different days. Our method in the experiments achieved excellent recognition of EER=0.06%. The agri-biometric authentication we propose accomplishes 'verifiable' agri-food traceability and brand protection; once the producers register pictures of their products into the database, anyone can verify the products on hand with the camera of a mobile phone.

1 INTRODUCTION

1.1 Product Identification for Traceability and Anti-Counterfeit

There have been growing demands for agri-products that have diverse added values including those originating from branded varieties, well-known growing districts, premium grades, and organic cultivation. Advertising these added values is now important for marketing, and gaining the trust of consumers is mandatory to sell products at high prices. The problem is that consumers, and even retailers and traders, cannot find these added values by just looking at the products themselves. Thus, product information has more impact on the price than the product itself, and this explains why counterfeiting is so enticing.

Increasing problems with counterfeited and fake products are being reported as the supply chain expands globally and internationally. These not only misappropriate revenues from the sales of genuine producers, but they can also have significant consequences on consumers. Consumers are currently having to pay a great deal of attention to traceability, which is the ability to trace the history of a product through all its stages of production, processing, and distribution.

Traceability is established based on methods of identifying and verifying individual examples of the product. We not only need to search databases, but also to verify that individual products on hand are genuine and not counterfeits. The way products are authenticated, identified, and verified determines the accessibility and anti-counterfeit capabilities of traceability systems.

The traditional way of identifying products is by attaching tags that directly display product information or serial numbers. Barcodes and RFIDs have recently been used to improve accessibility (Regattieri, 2007). As barcodes can be read by cameras installed on standard mobile phones, these offer greater access to consumers to obtain detailed information on products through the Internet. Although these technologies may provide increasingly more information, which may ease consumer confidence, the risk of counterfeiting is not reduced.

RFIDs and hologram tags have been proposed as

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technologies to combat counterfeiting (Bernardi, 2008). Chromatography and DNA analysis techniques have been conducted to inspect agri-products themselves to prevent counterfeiting (Lees, 2003). Numerous anti-counterfeit technologies have been utilized, and surveillance has been conducted by public institutions. However, counterfeiting of various agri-products is increasingly being reported.

1.2 Problems in Traceability of Agri-Product

Existing methods encounter two main difficulties in being effective deterrents against counterfeiting:

- Cost of tagging

Anti-counterfeiting tags are inexorably expensive and an enormous number of tags needs to be attached to all agri-products. The risk of tags being swapped cannot be avoided even after this high cost is incurred.

- Usability of verification

As inspecting tags and products require special devices or skilled staff, only limited numbers of products on the global market can be checked. Consequently, counterfeiting is rarely discovered. Consumers are not only unaware of anti-counterfeiting measures but they do not want to pay for these.

A novel method is required to solve these problems so that agri-products can be authenticated by anyone, anywhere, and at any time without having to rely on costly tags or inspection procedures.

1.3 Agri-Biometric Authentication

We propose a new methodology in this paper to identify individual agri-products by having single photographs taken of rind patterns (e.g., net, stripe, and dot patterns on the rinds, see Figure 1) and by matching these to an image database of authenticated products. Since methods of authenticating people using facial and fingerprint features are called 'biometrics', we have called our proposed method 'agri-biometrics'. The new method authenticates the fruit bodies themselves through the use of rind patterns, without the need to attach tags. Rind patterns of fruit are generated depending on the environment in which they are grown, and these are unique to individual fruit. Even if fake fruit are grown from the same seed and with the same method of cultivation, creating an identical rind pattern is supposed to be impossible. Thus, fake fruit cannot be cultivated, at least not within reasonable costs that would offset the expense of counterfeiting.

The key feature of the proposed method is that only a single photograph is required that is taken with handy standard cameras such those in mobile phones to authenticate the individual fruit on hand from the enormous amount of fruit on the market. Producers in practical traceability systems register images of shipped fruit into a database. As many producers adopt automated systems for grading and inspecting the quality of fruit (Kondo, 2010), capturing images of individual fruit in a database can easily be automated. If a traceability service to match images with those in the database is provided over the Internet, anyone can authenticate fruit using his/her smartphone from everywhere and at any time. As the whole market is monitored by everyone at all times, counterfeiting is expected to be effectively suppressed. Furthermore, as consumers are able to check the products themselves, they actually feel it is worth paying for added values.

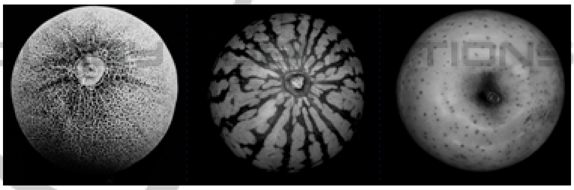

Figure 1: Rind patterns of netted honeydew melon, water melon, and green apple.

1.4 Previous Study and Proposed Architecture

In the literature, a similar approach has been reported. It identifies individual apples using appearances of multiple images (Niigaki, 2009). Since it requires numerous images to be taken for each authentication to compensate for different poses of apples, it is far from being a practical application. We propose a new method that normalizes pose variations to achieve authentication using only a single image, and that utilizes fingerprint matching technology to achieve extremely accurate authentication. Figure 2 outlines our new approach.

In our proposed method, a 3D model (sphere for melons) approximates a fruit’s average shape to an image and cancels out rotations in depth. This simulates the same process as that with fingerprinting, which also involves patterns on curved 3D surfaces that are flattened onto a scanner; the scanned image of the fingerprints does not contain deformation due to rotations in depth.

The rind patterns of fruit differ greatly from fingerprints, but their features have the common nature that feature points are located randomly for each individual, which is different from facial features. Our method extracts a feature set, which is compatible to the 'minutiae' used to match fingerprints, from a pose-normalized image. This make it possible to utilize state-of-the-art methods of fingerprint matching using minutiae features, whose accuracy has been demonstrated to be sufficient even for law enforcement applications (Jain, 2007).

In this study, which appears as the 1st report of agri-biometrics research, netted honeydew melons were chosen to be the targeted agri-product in this study. There are numerous premium brands, growing districts for melons, and the prices of melons differ from \$5 up to \$100 depending on such added value information. Thus the melon is considered to be a typical example of the agri-products having serious risks of counterfeits. We actually identified thousands of melons in the experiments to demonstrate high degrees of accuracy in practical situations.

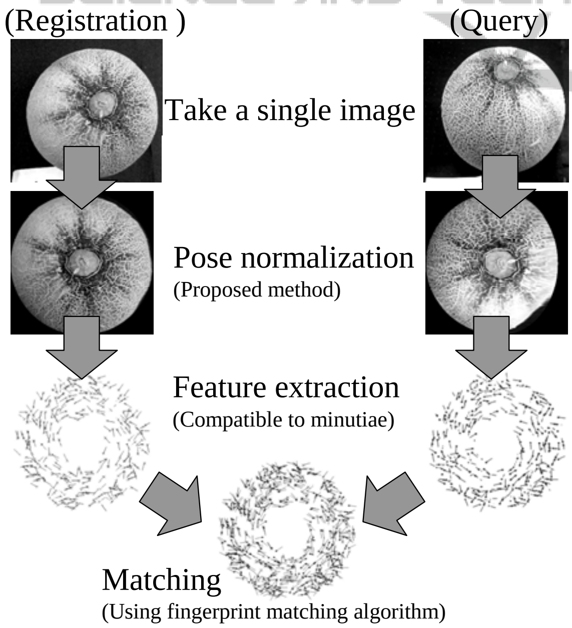

Figure 2: Architecture of our proposed method to authenticate the fruit using rind pattern image.

2 PROPOSED METHOD

A new method of authenticating fruit with agri-biometrics that uses a single image is proposed in this section. Our architecture utilizes the technique of fingerprint matching to match the rind patterns of fruit. It consists of three steps to make it feasible. The first step solves the problem of variations in object poses, which cannot be solved by conventional techniques of fingerprint matching. The second step extracts the feature set that is minutiae-compatible from the rind pattern image. The third step involves an extension of the conventional technique of fingerprint matching.

2.1 Pose Normalization

The pose normalization step in our proposed method is described in this subsection. As outlined in Figure 3, this step is used to take an image with the location of its stem point as input, and it cancels out the rotations in depth of the image. The contour of the object is extracted in this step, and a standard 3D shape model is fitted to the image. The input image is mapped to the pose-normalized image with the texture-mapping technique, which simulates an image being taken by setting up the camera and the fruit accurately in a predetermined normal pose.

The camera is modelled with weak perspective, and a sphere is used as the standard 3D shape model for melons (which is good approximation of the 3D shape of melons, especially for the premium graded honeydew melons we used). Let us denote the image coordinates and the camera's optical axis to correspond to the *x*, *y*, and *z*-axes. The normal pose is predetermined as the 'top view', where the melon's axis piercing from its stem point to the base is aligned with the *z*-axis.

Suppose that point P is on the sphere's surface and this corresponds to pixel (x_n, y_n) in the pose-normalized image, and that α denotes the angle between the line passing through the sphere's center to point P and the *yz*-plane. Also suppose that β denotes the angle between the line and *xz*-plane. Here, the following equations are obtained.

$$x_n = \sin\alpha, \quad y_n = \cos\alpha \sin\beta. \tag{1}$$

If the sphere is rotated by angle θ around the *y*-axis, P is moved to a pixel corresponding to a point whose polar coordinates are ($\alpha+\theta$, β) on the sphere; its image coordinates (x_t, y_t) are then obtained as:

$$x_t = \sin(\alpha+\theta), \quad y_t = \cos(\alpha+\theta) \sin\beta. \tag{2}$$

If the sphere is additionally rotated by angle φ around the *z*-axis, the image pixel corresponding to P is moved to (x_s, y_s), which is obtained as:

$$x_s = x_t\cos\varphi - y_t\sin\varphi, \quad y_s = x_t\sin\varphi + y_t\cos\varphi. \tag{3}$$

Here, the contour of the melon is detected as a

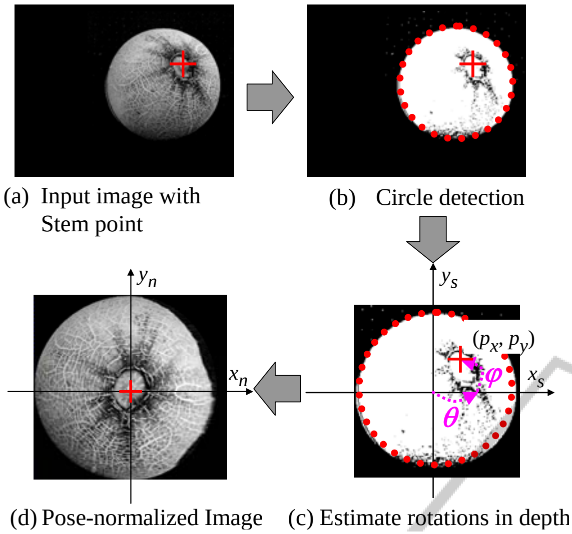

Figure 3: Pose normalization step in our proposed method to cancel out rotations in depth.

circle. For simplicity, we assume that the background of the image is dark monotone, thus the melon's body region is detected by applying the following well-known image processing algorithms: Otsu's digitization (Otsu, 1979) for the whole image, Canny edge detector, and Hough transform for circle finding (Figure 3(b)). In this study, the stem point is manually inputted. If its automation is necessary for the applications, numerous pattern-finding methods can be applied.

The original image is translated and scaled so that the detected circle is located at the origin and has a unit radius (see Figure 3(c)). If the stem point is located at (p_x, p_y), the rotations θ and φ, are estimated as:

$$\sin\theta = \sqrt{p_x^2 + p_y^2},\quad \tan\varphi = p_y / p_x \qquad (4)$$

The pose-normalized image (Figure 3(d)) is generated by calculating (x_s, y_s) for each pixel (x_n, y_n) and the pixel values are mapped from the input image. Although the input image has arbitrary rotations in depth (Figure 3(a)), the rotations are cancelled out in the pose-normalized image (Figure 3(d)).

2.2 Minutiae-Compatible Feature Extraction

This subsection describes the feature extraction step in our proposed method. As outlined in Figure 4, this step is used to extract a set of feature points and their directions. The feature set is compatible with the 'minutiae' that are widely used in fingerprint matching, and it can be matched with the state-of-the-art techniques of fingerprint matching.

First, the input image is digitized to extract the contours of the melon's netted rind pattern. Since the shading on the melon's surface differs locally and depends on the illumination environments in which the image was taken, locally adaptive threshold (Niblack, 1986) was adopted in digitization (a survey is given in (Sezgin, 2004)). This method determines the thresholds for each of all pixels based on the average and the variance in pixel intensities of each neighbouring pixels. The threshold was determined to be the local average plus the local standard deviation multiplied by a predetermined coefficient. The size of the neighbouring area and the coefficient were fixed for the all images. The fixed size and coefficient were determined in a preliminary experiment using separated image database to be sufficient to work well for extracting the mesh rind pattern from any image taken in general indoor environments.

After digitization, the image was filtered by successive morphological operations of dilation and erosion, and a median filter was used to remove noise and to smooth the contours. There is an example of the resulting image in Figure 4(b).

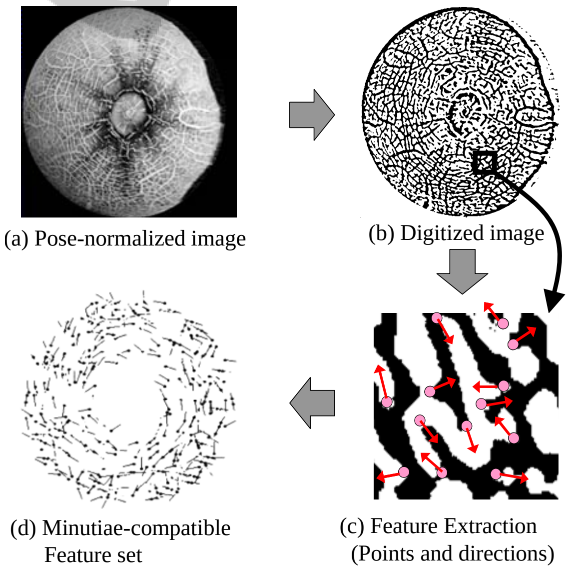

Figure 4: Feature extraction step of our proposed method to extract minutiae-compatible feature set from pose-normalized rind pattern image.

Next, our proposed method was used to extract image features that were compatible with the 'minutiae'. A minutia consists of the location of a feature point and the direction attached to it. Pixels on borders are traced to calculate the curvature to extract such features. If the curvature takes a local maximum that is larger than the predetermined threshold, the pixel is extracted as a feature point. The normal direction of the border at the feature point is determined to be the 'direction' of the feature point (see Figure 4(c)). Tracing all the borders of the rind pattern yields a set of hundreds of feature points and their directions, as shown in Figure 4(d). The set is compatible with 'minutiae'.

The feature points are extracted from a region that looks like a doughnut, as seen in Figure 4(d). The stem point region is omitted because it has few feature points that looks similar all over individuals.

2.3 Matching Image Features with Fingerprint Matching Technique

This subsection describes the feature matching step in our proposed method, where the similarity in pairs of images is evaluated by matching their feature sets using a state-of-the-art technique of fingerprint matching.

We propose utilizing the conventional algorithm originally proposed for fingerprint identification using the accidental coincidence probability (Monden, 2002), which is referred to as ACP in the following. The object pose in our applications is always unstable and varying numbers of feature points are missing in every match. ACP offers hope in such situations, because it has been shown to output a stable similarity score regardless of missing features. We have to ensure that ACP is based on the assumption that there is no correlation between the patterns of different individuals. Fortunately like fingerprints, the features of rind patterns of melons (and many other fruit) conform to this assumption, as fingerprints do.

How the ACP algorithm evaluates the similarity score is summarized here. Suppose that two feature sets, P_i and P_t consisting N_i and N_t feature points, respectively, are matched by determining their common corresponding feature points, whose locations and directions are sufficiently similar after applying global affine transformation between the two sets. It is assumed that any pair of feature points in either set is more distant than 2*d*. The threshold of the distance to determine corresponding feature points is *d*.

When P_i is a random pattern, i.e. N_i feature points are randomly located in the area of *S*, the probability that *n* feature points out of N_i will accidentally correspond to any of N_t feature points in P_t, i.e., the distance is less than *d*, is estimated as:

$$p(n; N_t, N_i, N_p) = \frac{\binom{N_t}{n}\binom{N_p - N_t}{N_i - n}}{\binom{N_p}{N_i}} \quad (5)$$

,

where N_p is an integer that is defined as:

$$N_p = \left\lceil \frac{S}{\pi d^2} \right\rceil \quad (6)$$

Therefore, when P_t is matched to any random pattern P_i, the probability that more than *N* corresponding points will be accidentally determined is estimated as:

$$p_{far}(N; N_t, N_i, N_p) = \sum_{n=N}^{\min(N_t, N_i)} p(n; N_t, N_i, N_p) \quad (7)$$

The p_{far} in Equation 7 indicates ACP. Since the smaller value for p_{far} leads to a higher likelihood of the coincidence of patterns P_t and P_i, we use (1-p_{far}) as the similarity score.

3 EXPERIMENTS

A total of 1,776 honeydew melons of the same strain, i.e., it was difficult to identify individuals, were collected to construct a large-scale image database for the experiments (there are examples in Figure 5). The experimental results obtained from authenticating the melons indicated that the proposed method of pose normalization made it feasible to apply the technique of fingerprint matching to match images of melons, i.e., 3D objects. The proposed approach significantly improved the accuracy of authentication.

3.1 Experimental Setup

The experiments simulated a realistic situation in which a melon producer registered images of melons into a database when they were shipped, and a consumer took an image with the camera of his mobile phone to authenticate the melon at a retail store. Four main changes inevitably occur in the two images to be matched for authentication in such practical use:

- Camera device
- Pose of melon
- Illumination environment
- Melon's colour and shape (subtle changes due to passage of time in supply chain)

The image database consists of the two sets: the registration set and query set which is taken two or three days later in a different location, by a different camera. Photographers were directed to take images from the tops of stem points to construct the image database, but no instruments were used to control the pose of the melon or the camera. A melon was directly placed on a desk, and an image was captured with a hand-held camera. Consequently, the camera axes of images were slanted by 10 degrees on average from the melon's vertical axis. Figure 5 has example photographs in the registration and query sets. The two images in the same column are of the same individual honeydew melon.

The resolution of the images was reduced to 640 x 640 at the beginning of the feature extraction step (see Section 2.2).

One query image of an individual melon was matched with one registration image of the same fruit in the experiments and 1,775 registration images of other individual melons. Consequently, 1,776 genuine pairs and 1,775 x 1,776 = 3,154,200 imposter pairs were matched in the experiments to evaluate the accuracy of authentication using the false accept rate (FAR) and false reject rate (FRR). To evaluate the rank recognition accuracy, an error was recorded if any of the imposter pairs including the query individual had a higher score than a genuine pair, which should have been ranked first.

3.2 Experimental Results

We compared our proposed approach with a conventional method that applies fingerprint matching without the pose normalization step described in Section 2. The recognition accuracies for the two methods are compared in Table 1 and Figure 7. Figure 7 plots the ROC curves whose horizontal axis indicates FAR and vertical axis indicates FRR. Table 1 also lists the first-rank matching error percentages (percentages of genuine pairs whose scores were less than any of the imposter pairs including each individual query).

The method without pose normalization resulted in a first-rank matching error of 3.1% and an EER (Equal Error Rate: the error rate (expressed as a percentage) when the authentication threshold was set so that FAR and FRR were equal) of 1.5%. These accuracies were much inferior to those reported in the studies of fingerprint matching techniques, which indicate that such direct application of fingerprint matching is not sufficiently rigorous.

In contrast, the first-rank matching error rate and EER (expressed as a percentage) were drastically reduced to 0.06% using our proposed pose normalization. Even when the authentication threshold was so rigorous that FAR=1.E-6 (one error in a million), FRR still remained quite low (0.06%). This implies that our proposed method offers anti-counterfeit checking that is so accurate that it only allows one in a million fake products, with only 0.06% error in the authentication of genuine products.

Consequently, the experimental results demonstrated that our proposed method reduces the error in authentication down to less than 1/50 that induced by the direct application of fingerprint matching without the pose normalization, and it offers a practical error rate that is much lower than the results obtained from benchmark tests of fingerprint matching (Jain, 2007).

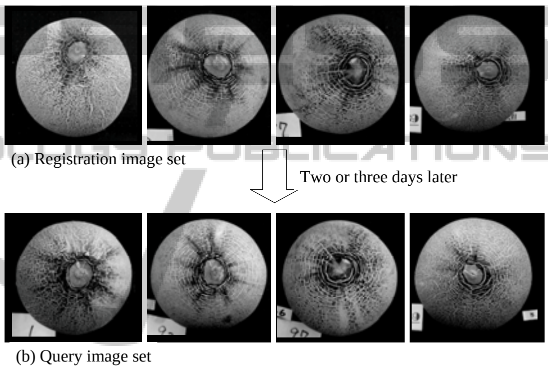

Figure 5: Image database of netted melons for the experiments.

Table 1: Recognition accuracy of proposed and conventional methods.

	EER	FRR @FAR1.e-6	Top-rank ID Error
Proposed	**0.06%**	**0.06%**	**0.06%**
w/o pose-normalization	1.5%	5.6%	**3.10%**

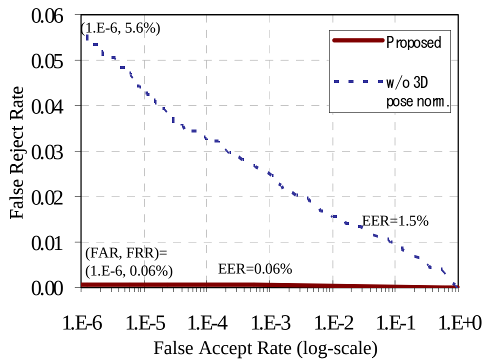

Figure 6: ROC curves to show the recognition performances of our proposed method (solid line) and conventional method (dotted line).

4 CONCLUSIONS

A new method of agri-biometric authentication was proposed to identify and verify individual pieces of fruit, using a single image of their rind patterns. We also proposed an architecture that normalized the rotations in depth of the target in the image, extracted minutiae-compatible features from a pose-normalized image, and then utilized a fingerprint matching technique to match the feature sets of images. The proposed architecture achieved excellent recognition accuracy in experiments using images of 1,776 honeydew melons.

Our new method enabled a traceability system to be attained that could protect fruit from being counterfeited without having to use wasteful and costly anti-counterfeiting tags. It would also enable anyone in a global supply chain to authenticate registered fruit with a standard camera from anywhere and at any time.

We chose melons as the first target in our research on methods of agri-biometrics authentication, because their 3D shape is simple and their rind patterns have an abundance of features. Our proposed architecture can be applied to various other fruit and agri-products. The two main requirements to apply our method are to model and fit a standard 3D shape model of the target to the image and extract the feature points and their directions from the rind pattern. Since the accuracy of recognition depends on uniqueness and the number of features in the rind pattern, we intend to investigate cases of other agri-products in future work to extend the applications of agri-biometrics.

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