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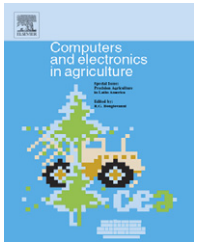

Assessment of retinal recognition technology as a biometric method for sheep identification

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ABSTRACT

In order to assure effective traceability, food-producing animals must be identified by a tamper-proof and durable technique. With the advance in human biometric technologies, the deployment of retinal recognition technology for cattle identification and verification has been prompted. The objective of this study was to assess the accuracy of a commercially available retina biometric technology for sheep identification (i) by determining whether light conditions during retinal image capture (indoors and outdoors with shade) and different operators exerted any significant effect on the matching score of the built-in pattern matching algorithm; and (ii) by evaluating the recognition performance of the biometric system for enrolment of one retinal image per sheep and two retinal images per sheep (bimodal biometric system). Neither the light conditions nor the operators were found to have a statistically significant effect on the matching score values of the built-in algorithm; yet it was clear that the pupillary light reflex phenomenon played a major role in obtaining lower matching score values for retinal images taken outdoors. The recognition errors of the one-retina biometric system were estimated to be 0.25% for false matches and 0.82% for false non-matches. An improved bimodal biometric system, i.e., two retinas, that applies a decision criterion based on a simple OR logical operator and a sum of matching scores, has been proposed in this study in order to reduce both probabilities of false matches and false non-matches to near zero.

1. Introduction

Recent animal health and foodborne illness scares in Europe along with the importance of export markets for national producers are creating a demand for source verification, food safety and supply chain identification of food products. Animal traceability refers to the ability to identify farm animals and their products according to their origin, as far back in the production sequence as is necessary to (i) ascertain ownership, (ii) identify parentage, (iii) assure food safety, and (iv) assure compliance (e.g., for source-verification, process-verification, production practice-verification, beef export verification and authenticity management). Obviously, animal traceability is completely dependent upon successful identification of individual animals or groups first and origin-and-movement records thereafter. Smith et al. (2005) pointed out that the drivers for livestock identification and traceability are (i) protecting herds and flocks—vigilance for disease to assure containment and to limit damages; (ii) promoting consumer confidence—to assure market access in global trade and to deliver on brand promise via added assurances and authenticity management; and (iii) adding value as a benefit

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of supply-chain management—preservation of intended value traits created by use of genetics, origin of production, unique inputs or processing methods.

In Ireland, the National Sheep Identification System (NSIS), which came into effect in June 2001, involves the individual identification of all sheep by ear tagging. However, any method of identification must not only be effective but must also safeguard the welfare of the animal. Many studies have shown that ear tags are very likely to cause both short- and long-term complications to the integrity of the ears, especially in sheep. Aslani et al. (1998) described an outbreak of tetanus in lambs instigated by plastic ear tags inserted too close to the base of the ears. After examination of the ears of over 700 sheep, Edwards and Johnston (1999) found that approximately 28% of the animals suffered slight to moderate ear damage associated with plastic ear tags, including local inflammation, pronounced thickening, traces of haemorrhaging and mild sepsis. In a later study, Edwards et al. (2001) compared the damage caused by inserting commonly used metal and polyurethane tags into the ears of ewes and lambs. They observed some incidence of tag loss due to the tag tearing through the ear and most significantly, they showed that the insertion of ear tags eventually resulted in an inflammatory response—and some discomfort and pain especially if the ear is handled when reading the tag. For complete food chain integrity, an animal marker should be able to identify the animal until its death. Recently (Fosgate et al., 2006), the results of a survival analysis modelling the rate of ear tags loss in buffalo – median ear tag retention of 272 days and an estimated ear tag loss rate of 0.0024 ear tags per day – has questioned the sufficiency of ear tags alone for long-term identification. On the other hand, electronic animal identification has certain limitations with regards to injection site in connection with migration problems and recovery in slaughterhouses (Eradus and Jansen, 1999).

While an animal can be allocated an identification number and the system of identification is made tamper-proof as far as possible, it may be necessary to verify an animal's identity against an invariant parameter in situations where the identity of the animal is in doubt (Dziuk, 2003). However, barcoded ear tags and electronic ear tags can be substituted from one animal to another, which lessens the reliability of verification. With the emergence and advance of human biometric technologies, a series of biometric markers for animal identification have been recently proposed and investigated, and they encompass DNA "fingerprinting" (Jiménez Gamero et al., 2006; Loftus, 2005), autoimmune antibody labels (Raschke et al., 2006), muzzle pattern (Barry et al., 2007), retinal vascular pattern (Rusk et al., 2006; Moss et al., 2004; Whittier et al., 2003), iris pattern (Musgrave and Cambier, 2002; Suzaki, 2001) and facial recognition (Corkery et al., 2007). As Shadduck and Golden (2002) pointed out, a robust biometric marker (physical, anatomical or biomolecular invariant trait that uniquely identifies a particular animal) (i) must be fraud-proof, (ii) must be rapid, inexpensive and accurate to capture, and (iii) must be non-invasive.

The retinal vascular pattern is a highly unique and distinct trait in livestock (De Schaepdrijver et al., 1989) and humans (Simon and Goldstein, 1935) that even differentiates monozygotic twins (Tower, 1955). In Whittier et al. (2003), retinal images of four cloned sheep from the same parent line were evaluated to confirm the uniqueness of the retinal vessel patterns in genetically identical animals. Masters (2004) explained the uniqueness of each individual's retinal vascular pattern by the theory that retinal angiogenesis obeys a Laplacian process that provides the randomness needed for fractal behaviour—the same branching patterns observed in rivers, trees, roots or erosion channels. With this theory, the probability of two retinal patterns being identical is virtually zero. Moreover, Shadduck and Golden (2002) indicated that the retinal vessels remain unchanged in the normally developing eye from birth to maturity. Although, there is strong evidence in favour to the suitability of retinal vascular pattern as a stable marker for livestock, very little work has been performed on assessing the recognition performance of this system. Rusk et al. (2006) evaluated the performance of the retinal imaging technology by verifying the identity of 317 4-H beef cattle and 220 sheep previously enrolled using this biometric system. Through a visual verification exercise (matching a pair of retinal images only visually), these researchers found a lower rate of false match (0.5%) and false non-match (1.6%) for beef cattle retinal images than for sheep retinal images (27.6% and 2.7%, respectively). While these researchers recognised the retinal imaging technology as viable for beef and sheep identification, additional research should be conducted to more closely gauge the error rates of this biometric.

To date, the Optireader device – developed by Optibrand™ (Colorado, USA) – is the only near-infrared ocular fundus digital video camera designed expressly for capturing retinal vascular patterns of livestock. Data Management software not only allows data storage and data organisation but also has the capability of comparing the branching patterns of two retinal images using a built-in pattern matching algorithm that produces a matching score value. The objective of this study was to assess the accuracy and suitability of this commercially available biometric technology for sheep identification (i) by determining whether light conditions during retinal image capture (indoors and outdoors with shade) and different operators exert any significant effect on the matching score of the built-in algorithm; and (ii) by evaluating the recognition performance of the system for enrolment of one retinal image per sheep and two retinal images per sheep.

2. Materials and methods

2.1. *Effects of light conditions and operators on the matching score*

A sample of 64 female sheep (ewes) was used for this experiment. They aged from 2 to 3 years and were cross-breed of Cheviot and Suffolk breeds. The trial work was carried out over a period of 6 weeks on a commercial farm during the summer months of June and July 2006. The ewes were divided into eight groups and retinal images were obtained from both eyes using the Optireader device (Optibrand, Colorado, USA). For each of the experiment's sessions – enrolment and recognition – 128 retinal digital images were obtained according

Table 1 – Experimental design for acquisition of retinal images from sheep grouped according to combinations of lighting conditions and operators for the sessions of enrolment and recognition

Group	Sheep	Retina	First retinal imaging (Enrolment)		Second retinal imaging (Recognition/Verification)	
			Operator	Light condition[a]	Operator	Light condition
1	1-8	1-16	1	1	1	1
2	9-16	17-32	1	1	2	2
3	17-24	33-48	2	1	2	1
4	25-32	49-64	2	1	1	2
5	33-40	65-80	1	2	1	2
6	41-48	81-96	1	2	2	1
7	49-56	97-112	2	2	2	2
8	57-64	113-128	2	2	1	1

[a] Light conditions: 1, outdoors with shade; 2, indoors. Shaded rows indicate that the conditions of retinal image capture were the same for the enrolment and the recognition sessions.

to combinations of two light conditions and two operators (Table 1). The light conditions were (i) indoors, where the ewes were restrained in a holding pen; and (ii) outdoors with shade, where the ewes were restrained in an outside sheep crush with a portable plastic canopy (2.2 m × 1.5 m × 0.8 m) erected at the end of the gate where the images were taken. Light readings were recorded using a luminance meter (Minolta T-10, Minolta Co., Japan) and ranged 100–200 lux for the indoors condition and 300–350 lux for outdoors with shade. As training and experience have been shown to be important components to successfully collect retinal images using the Optireader (Whittier et al., 2003), before initiating the experiment, the two operators completed a total of 18 h of rehearsal (in 3 weeks) acquiring retinal images from sheep outdoors and indoors. This was accomplished with the purpose of optimising their skills in handling properly the Optireader unit to obtain good quality retinal images that could be used in this experiment. As shown in Table 1, different combinations of light conditions and operators were defined in four groups and arranged in such a way that 50% of the retinal images for recognition were acquired under the same conditions of the enrolment retinal images (shaded rows in Table 1). The grey-level retinal images, stored as a JPEG file with other encrypted information – date of acquisition, ear tag number, sex, location, operator, and first or second session – were transferred to a central database (supported by Data Management software version 4.0, Optibrand, Colorado, USA) for the subsequent matching trials of pairs of images using servers from Optibrand base via Internet connection. In this software, a matching score quantifies the degree of similarity between two retinal images on a scale of 0 (no match) to 100 (perfect match).

To assess the effects (if any) of lighting conditions and operators on the matching score of a retinal image pair, a Kruskal–Wallis test of equality of medians was applied to both data sets of light condition and operator (SAS version 8.2, SAS Institute Inc., NC, USA). A parametric analysis of variance was not considered appropriate as the matching score data did not follow a normal distribution and was still not normal after several data transformations including the Box–Cox method (Peltier et al., 1998). Each data set – light condition and operator – produced four levels that originated from the combinations of retinal images acquired for enrolment and for recognition. For instance, in the case of the light condition data set, the four levels defined for the Kruskal–Wallis test were: (1) outdoors during both enrolment and recognition, (2) outdoors during enrolment and indoors during recognition, (3) indoors during enrolment and outdoors during recognition, and (4) indoors during both enrolment and recognition.

2.2. *Recognition performance of the biometric system*

The objective was to assess the recognition performance of the retinal imaging and matching system for sheep retinal vascular patterns using the classical framework of statistical decision theory. Briefly, yes/no pattern recognition decisions have four possible outcomes: either a given pattern matches the target or does not match the target; or, in either case, the decision made by the recognition algorithm may be either the correct or the incorrect one. In a biometric decision context, the four possible outcomes are normally called false match, correct match, false non-match and correct non-match. Obviously the first and the third outcomes are errors (called Types I and II, respectively), while the second and the fourth outcomes are the ones sought. By manipulating the decision criteria – the matching score threshold – the relative probabilities of these four outcomes can be adjusted (Daugman, 2000).

In order to evaluate the recognition performance – false match error rate and false non-match error rate of the system – and to estimate a matching score threshold (ms*), a series of one-to-one comparisons of pairs of retinal images (matching trials) were performed. Firstly, the retinal images acquired during the recognition stage were compared to their respective pair acquired during the enrolment stage, producing a set of 128 matching scores. Secondly, matching trials were conducted between each of the retinal images of the verification set with seven randomly chosen images from the enrolment set (not belonging to the same eye). Thus, another set of 896 matching scores originated from pairs of different retinal images was produced. Parametric distributions were fitted to both the matching scores of retinal image pairs acquired from the same eye (genuine distribution) and the matching scores of retinal image pairs acquired from different eyes (non-genuine distribution), using EasyFit version 3.0 (Mathwave Technologies, Ukraine). The procedure to estimate the false match error rate, false non-match error rate, the matching score threshold (biometric decision landscape) and the receiver operating

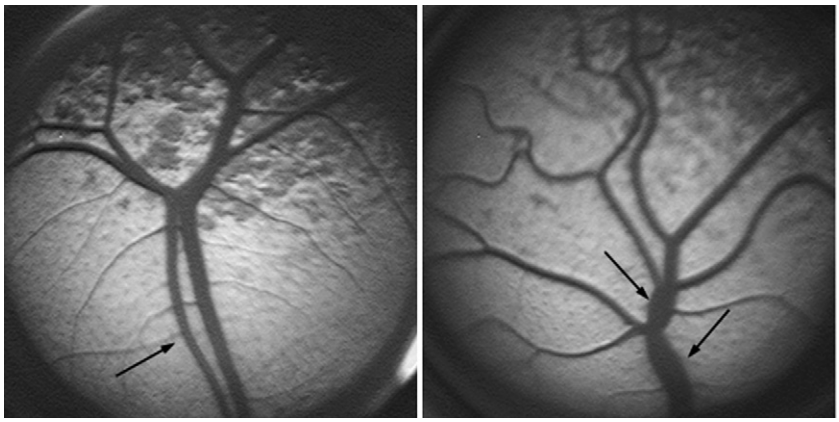

Fig. 1 – Examples of pairing and twisting of large vessels, a phenomenon normally observed in sheep retinal vessels.

characteristic curve (ROC) from the matches distribution and the non-matches distribution is outlined in Delac and Grgic (2004). Finally, a decision analysis for a multimodal biometric system based on two retinal images per sheep has been worked out based on a logical OR operator and a simple combined sum of matching scores so as to improve the probabilities of correct match and correct non-match to ~1.

3. Results and discussion

3.1. *Effects of light conditions and operators on the matching score*

Fig. 1 shows two characteristic images of the vascular pattern of sheep retina. The presence of areas of dark pigmentation in the ocular fundus was noticed in most retinal images, in agreement with Ollivier et al. (2004). From fluorescein angiography images, Galán et al. (2006) deduced that sheep's retinal vascular patterns have three or four pairs of vessels (arteries or veins) – ventral, dorsal, ventronasal and ventrotemporal – and additional five to eight arterioles and venules radiating from the temporal and medial portions of the optic disk. In our sheep retinal images, the pairing of large vessels – more likely to be dorsal vessels due to their large size – occurred very frequently, and sometimes this pair twisted around each other (see arrows in Fig. 1). Unlike fluorescein angiography, the Optireader does not capture the optic disk but the major vessels that emerge from it and their ramifications going towards the temporal and medial region of the fundus. It is precisely this random arrangement of vessels, arterioles and venules what imparts uniqueness to this biometric.

The matching scores obtained from every pair of retinal images acquired from the same animal underwent a Kruskal–Wallis test to ascertain possible influences of light conditions during image acquisition and operators. The results showed that neither the light conditions nor the operators had a significant effect on the degree of image matching, i.e. on the matching score value (Table 2). Although the mean value of the matching scores from pairs of images taken indoors (enrolment and recognition performed indoors; ms = 95.63) was substantially higher than the mean matching scores from pairs of images taken outdoors (enrolment and recognition performed outdoors; ms = 89.75); this difference was not large enough as to produce statistical significance. This discrepancy of matching scores between images taken outdoors and taken indoors was primarily due to the pupillary light reflex phenomenon, which originated certain differences in image quality (with the assumption that the tree-like vessel pattern was properly positioned within the image). Most retinal images taken outdoors (300–350 lux) were slightly less sharp than the images taken indoors (100–200 lux).

The difficulty in obtaining retinal images in bright light arises due to the pupillary light reflex phenomenon—i.e., the size of the pupil being controlled by involuntary contraction and dilation of the iris, in order to regulate the intensity of light entering the eye. The sheep iris, made of muscles, changes the size and shape of the pupil; but instead of varying from a small circular opening in bright light to a large circular opening in dim light, like in humans, the sheep's pupil remains wide, and only varies in height. As the light becomes dimmer, the sheep's pupil changes to an oval shape; while, in bright light, the pupil has a peanut-like shape and its size is reduced to roughly (1/3)–(1/4) of its normal size in dim conditions (Fig. 2). The smaller size of the pupil for the capture condition outdoors with shade caused a significant difference ($p < 0.05$) in the time to capture retinal images[1] between the two light conditions. The mean and standard deviation values for the retinal image capture outdoors with shade were 67.85 s and 70.12 s, as opposed to the indoors condition: mean value of 50.38 s and standard deviation of 47.85 s (Table 3). This mean time for indoors image capture (50.38 s) agreed closely with a previously reported value of 56.03 s for retinal image capture in sheep (Rusk et al., 2006).

[1] Image capture time given by the Optireader, which is defined as the moment the targeting is activated until an image is captured that presents the operator with an acceptable quality image of the vein pattern. On some occasions, two to three retinal images were rejected before an image of acceptable quality could be obtained; while on other occasions, an acceptable retinal image was acquired at once. Therefore, the image capture time given here should not be regarded as the average time to obtain one retinal image.

Table 2 – Results of the Kruskal–Wallis test for user and light condition, and mean values of matching scores from retinal image pairs acquired indoors, outdoors and outdoors/indoors

Combination	N	Median	Average rank	Z	H	Pr > H
Operator					7.25	0.064
1[a]	32	93.47	53.8	−1.88		
2[b]	32	93.35	61.3	−0.56		
3[c]	32	94.42	64.8	0.06		
4[d]	32	97.73	78.0	2.39		
Light					6.17	0.104
1	32	93.19	55.8	−1.53		
2	32	94.00	61.6	−0.50		
3	32	94.67	62.8	−0.30		
4	32	97.70	77.8	2.33		
Mean values of matching scores per group						
Enrolment outdoors/recognition outdoors (25% of total data)						89.751
Enrolment outdoors/recognition indoors (25% of total data)						93.456
Enrolment indoors/recognition outdoors (25% of total data)						93.554
Enrolment indoors/recognition indoors (25% of total data)						95.631
Total average (all data)						93.098

[a] Retinal images acquired outdoors during both enrolment and recognition.
[b] Retinal images acquired outdoors during enrolment and indoors during recognition.
[c] Retinal images acquired indoors during enrolment and outdoors during recognition.
[d] Retinal images acquired indoors during both enrolment and recognition.

3.2. *Recognition performance of the biometric system*

The histograms of frequencies of matching scores are shown in Fig. 3. The non-genuine histogram was built from the 896 non-genuine matching scores (comparison between two retinal images taken from different sheep; Fig. 4), while the 128 genuine matching scores (comparison between two retinal images taken from the same sheep's eye; Fig. 5) were used to build the genuine histogram. As normally occurs in all biometric decision landscapes (Daugman, 2000), a certain degree of overlap between the two histograms was observed. In order to obtain a good estimate of the errors associated with this overlap area, two continuous distributions were fitted. The data set of the non-genuine matching fitted a Beta general distribution ($\alpha_1 = 2.5293$, $\alpha_2 = 4.1594$, minimum = 27.1112, maximum = 77.1739) while the data set of the genuine matching fitted a generalised extreme value distribution ($k = -0.8802$, $\sigma = 7.1609$, $\mu = 93.1580$). A matching score threshold (ms^*) is a cut-off value with which any matching score can be compared in order to accept or reject a claimed identity. A ms^* value of 70 was found to minimise the false match error (probability of mistaking two images from different retinas to be from the same retina) and the false non-match error (probability of mis-

Fig. 2 – Sheep's pupil varying from oval shape in dim light conditions to peanut-like shape in bright light (outdoors without shade).

Table 3 – t-Test results for difference in image capture time between the conditions indoors and outdoors with shade (unequal variances between groups)

Condition	Mean (s)	Standard deviation (s)	Standard error mean (s)
Outdoors with shade	67.85	70.12	6.24
Indoors	50.38	47.85	4.33

Estimate for difference	17.47 s (outdoors – indoors)
95% CI for difference	2.49–32.46
d.f.	221
t-Value	2.30
P-Value	0.022

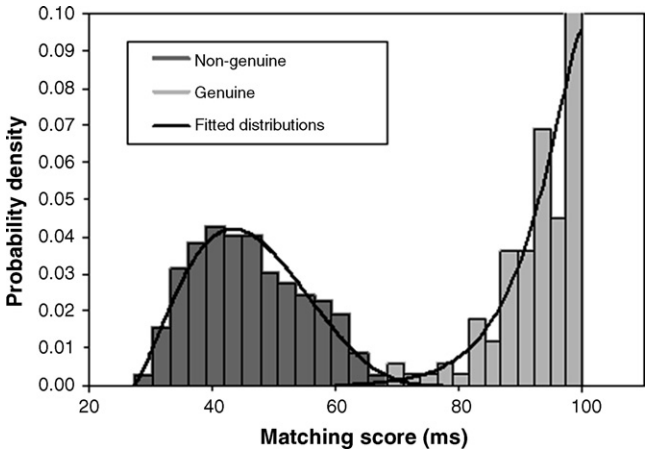

Fig. 3 – Genuine and non-genuine distributions fitted from histograms of matching scores obtained from image pairs taken from the same retina ($n = 128$) and image pairs taken from different retinas ($n = 896$).

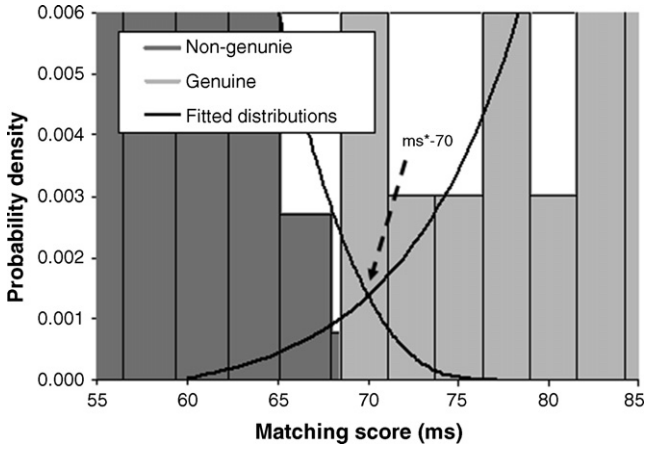

Fig. 6 – Enlarged detail of the overlap area in Fig. 3 between non-genuine and genuine distributions showing optimal matching score threshold.

taking two images from the same retina to be from different retinas), as can be seen in Fig. 6.

In addition, from the distributions overlap (Fig. 6), false match error values and false non-match error values were calculated for other matching scores ranging from 61 to 75 in order to construct a receiver operating characteristic (ROC) curve. Each point of this curve (Fig. 7) represents a different decision strategy, i.e. the trade-offs that can be achieved between false match error and false non-match error. The overall performance of the retinal recognition system for sheep can then be judged by how bowed the ROC curve is. In an ideal biometric system, the ROC curve would be extremely bowed, reaching as far as possible into the lower left corner of

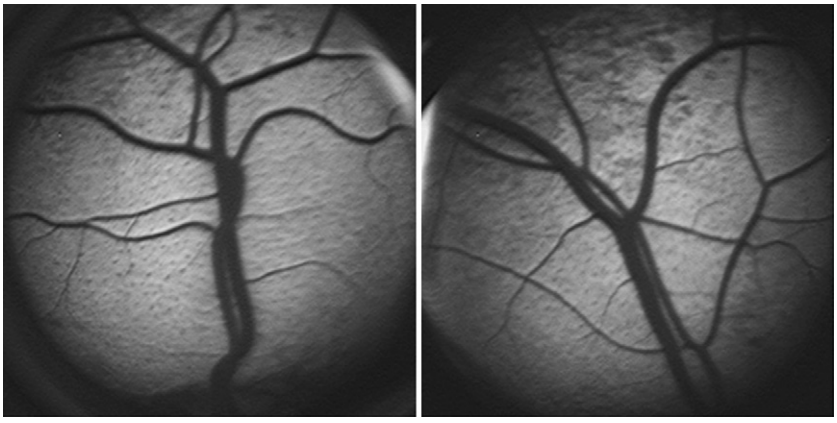

Fig. 4 – A case of correct non-match of sheep retinal images (matching score = 50.25).

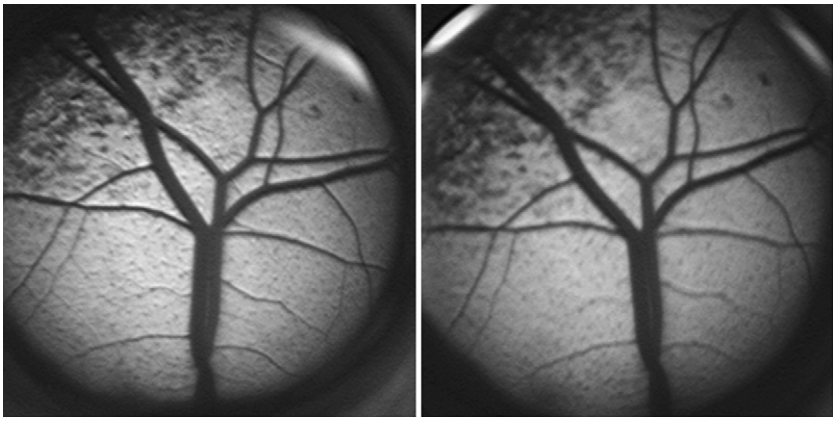

Fig. 5 – A case of correct match of sheep retinal images (matching score = 100).

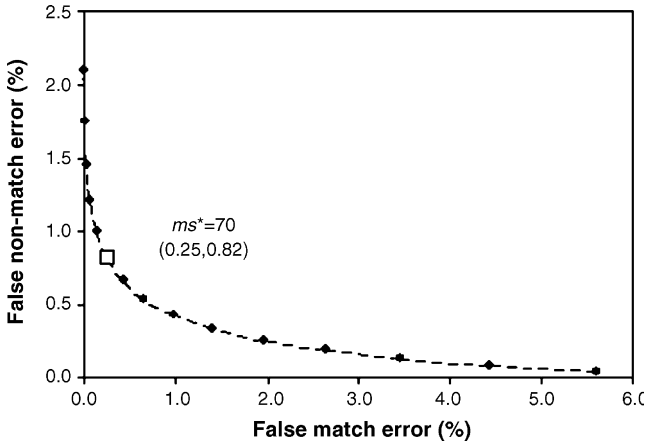

Fig. 7 – Receiver operating characteristic (ROC) curve showing matching score threshold (ms*) that minimises false match error and false non-match error.

Fig. 7, since reaching that limit would correspond to achieving a correct match rate of 100% while keeping the false match rate at 0%. With a ms* of 70, the estimated false match error of the system was 0.25% while the estimated false non-match error was 0.82%. When this ms* was regarded as the cut-off point for the decision criterion (i.e., *if* the value of ms obtained from any matching trial is higher than or equal to ms*, *then* the compared retinal images belong to the same animal) of 128 genuine matches and 896 non-genuine matches, two cases of false match and two cases of false non-match were observed. Fig. 8 presents a case of false match, i.e., although retinal images were taken from different sheep, the decision criterion failed to generate a correct non-match because their matching score (73.61) was higher than ms* (70), due to certain similarities in the branching pattern. In contrast, although the pair of retinal images shown in Fig. 9 were taken from the same sheep's eye, the value of their matching score (68.52) did not convey a correct match when compared to ms*, but instead a false non-match. From Fig. 9, it can be inferred that the position of the tree-like structure (circles in both images) and again the image quality (mentioned in the previous section as the factor causing lower matching scores for images taken outdoors) in fact can lead to matching errors.

So far, based on the results obtained, it can be said that the vascular pattern of a single retina can be used as a biometric marker for sheep identification or verification with good matching accuracy. Retinal images have been relatively easy to acquire – evidently depending heavily upon light conditions – and the fact that normally the same views of the tree-like pattern were obtained, greatly facilitated the correctness of the matching process. Although sheep needed to be restrained, the biometric acquisition is non-invasive as reti-

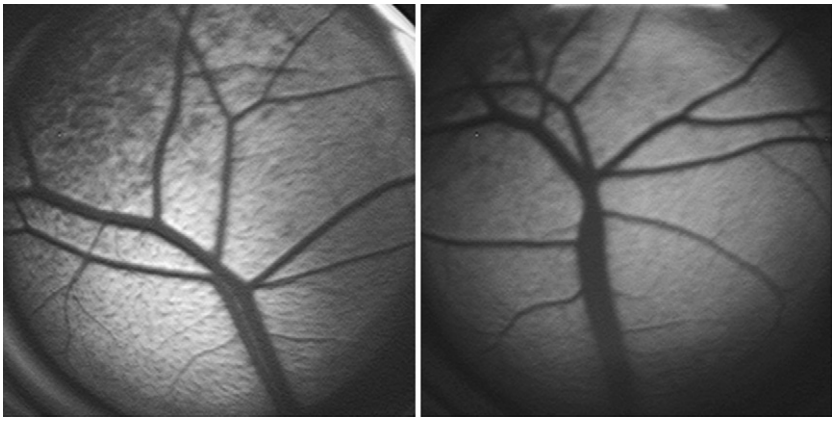

Fig. 8 – A case of false match (ms = 73.61) for a matching score threshold of 70.

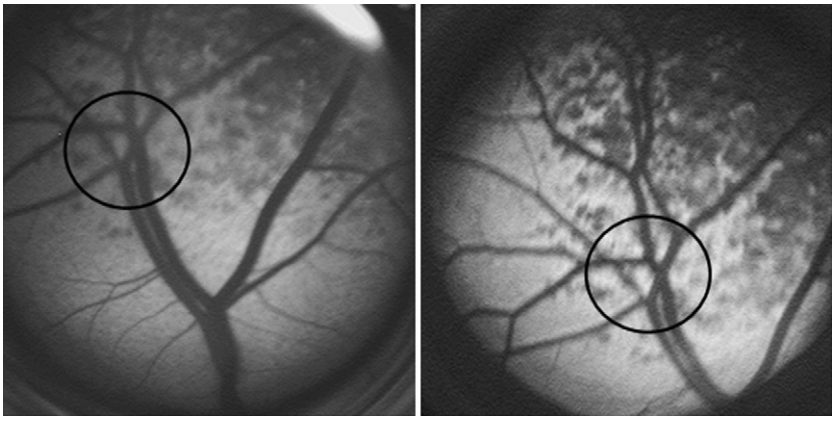

Fig. 9 – A case of false non-match (ms = 68.52) for a matching score threshold of 70. Circles show differences in position and in image quality that led to the matching error.

nal patterns could be imaged at a distance of 1–2 cm from the pupil. In terms of performance, this biometric system has demonstrated to be accurate as suggested by the low error rates associated with the use of one retina per individual for identity verification. Moreover, this accuracy (probabilities of 0.9918 of a correct match and 0.9975 of a correct non-match) can be further improved by acquiring two retinal images per individual (from both eyes) instead of only one. The next section briefly introduces the concept of multimodal biometrics and examines the improvement in recognition performance that can be attained when two retinal images per sheep are acquired.

3.3. *Performance of a bimodal retinal recognition*

The limitations arising from inter-class similarity (such as the two false match cases that occurred due to similarities in branching patterns; one case shown in Fig. 8) can be overcome by including multiple sources of information for establishing identity. Such systems, known as multimodal biometric systems, are expected to be more reliable due to the presence of two or more independent sources of information. In a single-biometric-trait/multiple-units scenario (Ross and Jain, 2004), information from two or more fingerprints (obtained from two or more fingers) or information of both irises of a single user can be fused in order to improve the system performance in an inexpensive way—as only one sensor and one matching module is used. In the case of sheep retina recognition, this would translate into acquiring images of both retinas for improved performance.

When information is fused at the *match score level*, two distinct strategies can be adopted (Sanderson and Paliwal, 2004). In the *concatenation or classification approach*, the fusion is viewed as a classification problem where a feature vector is constructed using the matching scores output of the individual matching modules; this feature vector is then classified into one of two classes: accept (genuine match) or reject (non-genuine match). In the *combination or summation approach*, the fusion is viewed as a combination problem where the individual matching scores are combined to generate a single scalar score which is then used to make a final decision. Ross and Jain (2003) showed that a simple summation (combination approach) gave better results in obtaining a significant improvement in the matching performance of a multimodal biometric system (fingerprint, face and hand geometry) than a classification approach (use of discriminant functions and decision trees). Alternatively, the information obtained from multiple classifiers can be also fused at the *decision level*. In this case, each matching module will individually classify into accept or reject; and the final decision can be made with AND & OR logical operators, majority voting or combination of ranked lists (Prabhakar and Jain, 2002).

In the particular case of two retinal images (right and left), the information fusion can be done at match score level or at decision level. At match score level, a summation approach of the matching scores of the individual right and left retinal modules can be performed ($ms_R + ms_L$). Information fusion can be done at decision level using the OR operator, since both retinal modules (right and left), being the same, are strong in terms of performance, are independent from each other, and

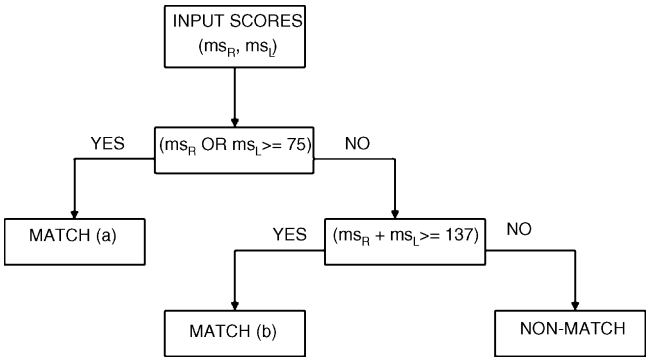

Fig. 10 – Enhanced decision criterion for matching based on two retinas producing virtually 0% mismatch errors.

their matching scores have the same possible range of values (if a weak biometric and a strong biometric were combined, information fusion using the OR rule would be rather inappropriate and information fusion using a simple sum of matching scores would be insufficient). Fig. 10 shows a schematic of the decision criterion adopted for the biometric system of two retinas, which was based on merging two approaches: information fusion at decision level (OR operator) and information fusion at match score level ($ms_R + ms_L$), in the form of a decision tree.

From the fitted genuine and non-genuine distributions (Fig. 6), it can be deduced that a ms* value of 75 produces a false match error of 0% at the expense of an increase in false non-match error to 2.0934%. However, setting the ms* to 75 in a combined biometric system will ensure a probability of correct non-match close to 1. The adoption of the OR-based conjoint decision will maintain the false match error in 0% and will reduce the false non-match error to 0.0438%[2] when the outcomes of the two retina matching trials are combined using a ms* of 75. With the two-retina recognition system, the false non-match error dropped from 0.82% (for a ms* of 70 for only one retina) to 0.0438% (for a ms* of 75), which is precisely what an ideal biometric system seeks (to increase the probability of correct match to a level close to 1; in the combined OR decision criterion, the probability of correct match has increased to 0.99956).

Because there is still a small probability of having a correct match when the matching scores (ms_R and ms_L) of the two pairs of retinal images are *both* lower than 75 (0.0438%); the second step of the decision criteria (Fig. 10) was to perform a simple sum of the matching scores of the right and left retinas ($ms_R + ms_L$) and compare it against a combined matching score threshold value (ms_{R+L}*). The procedure to find ms_{R+L}* was the same as the one followed for the single retina system. The non-genuine matches distribution ($n = 64$ matching trials) was fitted to a beta distribution ($\alpha_1 = 4.3160$, $\alpha_2 = 6.2704$,

[2] Let $P(FM)$ be the probability of a false match using only one retina, $P(FNM)$ be the probability of a false non-match using only one retina, $P_{RL}(FM)$ and $P_{RL}(FNM)$ be the probabilities of a false match and a false non-match, respectively, of the combined biometrics (right and left retina). Then $P_{RL}(FNM) = P(FNM)^2$ and $P_{RL}(FM) = 1 - [1 - P(FM)]^2$.

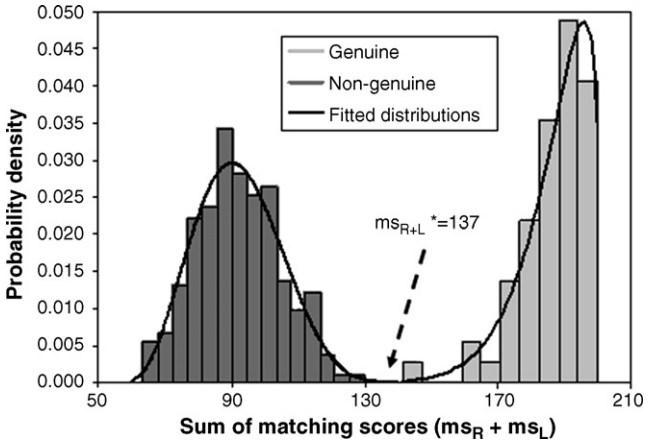

Fig. 11 – Genuine and non-genuine distributions fitted from histograms of combined matching scores obtained from two image pairs (right and left retina) taken from the same sheep (n = 64) and two image pairs taken from different sheep (n = 448).

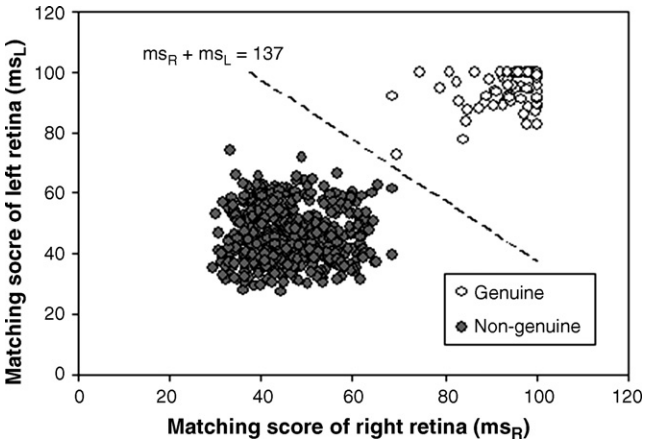

Fig. 12 – Scatterplot of matching scores of right and left retinas of the same sheep showing good separability between genuine matching (n = 64) and non-genuine matching (n = 448).

minimum = 56.1955, maximum = 144.1351) and the genuine matches (n = 448 matching trials) to a generalised extreme value distribution ($k = -0.76478$, $\sigma = 11.496$, $\mu = 185.85$). With a simple sum of matching scores ($ms_R + ms_L$), the errors associated with the distribution's overlap could be significantly reduced. Fig. 11 shows the outstanding separation between the genuine and non-genuine distributions for the combined matching score. In order to reduce the false match error of this combined system to 0%, a ms_{R+L}* value of 137 was established as the cut-off score. This ms_{R+L}* produced a false non-match error of 0.1318%.[3]

Consequently, having estimated the errors of the OR decision criterion and the errors of the ms_{R+L} decision criterion, the probabilities of correct match and correct non-match of the decision tree (Fig. 10) were also determined:

(i) Output of OR decision rule—match (a) in Fig. 10: Let s_1 and s_2 represent two pairs of retinal images acquired during enrolment and during verification, respectively. The probability of two sheep being different given that any of the matching scores are equal to or higher than 75, $P((s_1 \neq s_2)|(ms_R OR ms_L \geq 75))$, is 0, because the false match error of '$ms_R OR ms_L \geq 75$' is 0%. The probability of having a correct match given that any of the matching scores are equal to or higher than 75, $P((s_1 = s_2)|(ms_R OR ms_L \geq 75))$, is 1.

(ii) Outputs of '$ms_R + ms_L \geq 137$' decision rule—non-match and match (b) in Fig. 10: The probability of two sheep being different given that the sum of their retinal matching scores are equal to or higher than 137, $P((s_1 \neq s_2)|(ms_R + ms_L \geq 137))$, is 0, because the false match error of '$ms_R + ms_L \geq 137$' is 0%. On the other hand, a conjoint false non-match will occur only if both tests (OR and '$ms_R + ms_L \geq 137$') produce a false non-match. Therefore, the probability of having a correct match given that the sum of the retinal matching scores are equal to or higher than 137 is: $P((s_1 = s_2)|(ms_R + ms_L \geq 137)) = 1 - (FNM_{OR})(FNM_{msR+msL\geq 137}) = 1 - (0.000438)(0.001318) = 0.999999 \sim 1$ (FNM rate = $5.77 \times 10^{-7} \sim 1$ false non-match in 1.7 million matching attempts).

Thus, a two-retina biometric system for sheep identification achieved virtually a probability of correct match of 1 and correct non-match of 1 (since FNM = FM ~ 0% for the enhanced decision criterion). Fig. 12 illustrates that the ms_{R+L}* of 137, as an individual matching module, discriminated effectively between genuine and non-genuine matches without false matches or false non-matches for a sample size of 64 genuine matching scores and 448 non-genuine matching score (originated from 64 sheep). Nevertheless, the validity of this information fusion methodology (Fig. 10) should be further assessed on a large database of sheep retinas. While it can be argued that the capture of the two retinas during enrolment is time-consuming; the principal argument in favour to the two-retina recognition system is the performance superiority of the conjoint decision criterion which makes this system practically tamper-proof. Therefore, the biometric identifier based on a retinal recognition system has proven to be a very accurate identification method for sheep, particularly when two retinal images are acquired per individual.

3.4. *Recommendations for practitioners*

In order to consistently acquire sheep retinal images of good quality (sharp images having the retinal tree-like vascular structure positioned in the centre), the authors recommend at least 15 h of training. As in the case of other identifiers (application of ear tags, transponders or boluses), the animal needs to be restrained. Any holding pen or crush (race) that prevents excess movement of the animal's head is recommended. However, there is no need to hold the animal's head. Good retinal images, such as the ones shown in Figs. 4 and 5, are obtained

[3] False non-match error of the summation criteria only.

Fig. 13 – Procedure for acquisition of retinal images of sheep. Once the animal is restrained, the retinal camera is pointed at 1.0–1.5 cm from the eye in the direction of the opposite ear.

when the retinal camera, at 1.0–1.5 cm from the eye, is pointed in the direction of the animal's opposite ear (Fig. 13). The capture time of individual images has been found to be variable from sheep to sheep, depending on animal's age, animal's breed and stress.

4. Conclusions

Although the mean value of the matching scores from pairs of images taken indoors (ms = 95.63) was substantially higher than the mean matching score from pairs of images taken outdoors (ms = 89.75); this difference was not sufficiently large as to produce statistical significance. The discrepancy in matching scores between images taken outdoors and images taken indoors and the significant difference ($P < 0.05$) in retinal image capture time between light conditions is due to the pupillary light reflex phenomenon. Depending on the level of bright light, this phenomenon can make image acquisition simply unfeasible. However, this study has shown that the use of a simple portable shelter outdoors can provide shade enough (300–350 lux) to facilitate the capture of retinal images. On the other hand, no significant operator effects on the matching score values were found. The analysis of the performance of the one-retina biometric system for verification of sheep identity, using classical statistical decision theory, led to the estimation of two error rates (false match error and false non-match error) for different thresholds of matching score. The matching score that minimised the system's errors was found to be 70 (estimated false match error = 0.25% and estimated false non-match error = 0.82%). In an attempt to enhance the system's recognition performance, i.e., increase the probabilities of correct match and correct non-match to ~1, we investigated an improved biometric system for sheep identity verification based on two retinal images being scanned per individual during enrolment. An enhanced decision criterion accomplishing information fusion at match score level and at decision level has been proposed in this study: first, using an OR logical operator compared against a high matching score (75) ensured absence of false matches; and second, using a simple sum of the matching scores (from the matching trials of the two retinas) was discriminant enough to separate genuine from non-genuine, and along with the OR operator, it minimised the probability of encountering false non-matches to $\sim 5.77 \times 10^{-7}$. While the validity of these results should be further assessed on a large database of sheep retinas, this preliminary assessment demonstrated the potential of retinal recognition technology for sheep identification, and that the best performance can by far be achieved by acquiring two retinal images per sheep.

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