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Review

From classical methods to animal biometrics: A review on cattle identification and tracking

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ABSTRACT

Cattle, buffalo and cow, identification has recently played an influential role towards understanding disease trajectory, vaccination and production management, animal traceability, and animal ownership assignment. Cattle identification and tracking refers to the process of accurately recognizing individual cattle and their products via a unique identifier or marker. Classical cattle identification and tracking methods such as ear tags, branding, tattooing, and electrical methods have long been in use; however, their performance is limited due to their vulnerability to losses, duplications, fraud, and security challenges. Owing to their uniqueness, immutability, and low costs, biometric traits mapped into animal identification systems have emerged as a promising trend. Biometric identifiers for beef animals include muzzle print images, iris patterns, and retinal vascular patterns. Although using biometric identifiers has replaced human experts with computerized systems, it raises additional challenges in terms of identifier capturing, identification accuracy, processing time, and overall system operability. This article reviews the evolution in cattle identification and tracking from classical methods to animal biometrics. It reports on traditional animal identification methods and their advantages and problems. Moreover, this article describes the deployment of biometric identifiers for effectively identifying beef animals. The article presents recent research findings in animal biometrics, with a strong focus on cattle biometric identifiers such as muzzle prints, iris patterns, and retinal vascular patterns. A discussion of current challenges involved in the biometric-based identification systems appears in the conclusions, which may drive future research directions.

Contents

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1. Introduction

The need for cattle identification has become a twofold problem that encompasses human health, as well as cattle preservation, management, and increased production. Cattle can be reared in different locations and can be frequently traded before they are eventually slaughtered. The slaughtering process itself may take place far away from the original place of rearing, and it may lack accredited information about the actual source of the cattle. The freedom of livestock movement increases the risk of spreading livestock diseases, resulting in the contamination of meat products (Sofos, 2008). Meats of unknown origins, a lack of knowledge about the cattle's health status, and contaminated meat products all pose a high risk to the health of meat consumers. Consequently, knowing the sites of origin of a beef animal is a significant factor for judging the health status of the beef animal and the quality of the meat products.

Confirming the health of a living cattle, and detecting any diseases early, increases the consumer's awareness and meets their demands for source verification, food safety, and supply-chain identification of meat products (Zhao et al., 2011). The current situation highlights the need for efficient and secure identification and tracking systems, not only for living beef animals but also for the animal products (Marchant, 2002; Sofos, 2008). On-farm identification and off-farm traceability of beef animals can improve the ability to identify each farm and its products at every step from farm to fork. Public health authorities can utilize information from the identification systems to effectively detect any sources of contamination in meat products.

Cattle identification systems have widespread beneficiaries, from animal producers and consumers to the food industry itself. These systems help to limit the spread of animal diseases by effectively controlling animal vaccination and allowing for a better understanding of disease trajectories, limiting livestock producers' losses to disease, reducing the costs of governmental disease eradication, minimizing potential trade losses, and facilitating ownership management (Geers, 1994; Sofos, 2008; Vlad et al., 2012).

The development of animal identification systems began at the end of the 1960s by different researchers, while the first results were presented only in 1976 (Rossing, 1999). Traditional cattle identification methods such as ear notching, tattooing, and branding are not sufficiently reliable in cattle identification because they are susceptible to theft, fraud, and duplication (Klindtworth et al., 1999). Electrical identification methods, particularly Radio Frequency Identification (RFID) (Roberts, 2006), emerged later than the classical methods and are characterized by higher reliability; however, they also present security, installation, and operational challenges. Monitoring and tracking cattle's physiological and behavioral characteristics can supplement the utilization of cattle identification systems (Frost et al., 1997). Therefore, the need for a more robust cattle identification scheme has become desirable.

Biometrics, a science that is currently used to identify humans, is a promising trend in the cattle identification domain. Animal biometrics has many applications, including classifying cattle, tracking cattle from birth to the end of the food chain, and understanding animal disease trajectories and population patterns. Deploying animal biometrics into computerized systems currently faces challenges with respect to identification accuracy and the system's robustness, given that animal movements cannot be easily controlled. Thus, addressing the current challenges facing biometric-based cattle identification systems would eliminate several problems inherent to the classic identification methods and RFID-based identification technology.

This article presents a review of cattle identification in terms of traditional identification methods, new identification trends, and current challenges, by shedding light on human biometrics as an important basis for animal biometrics. Although some earlier reviews can be found in the literature (Neary and Yager, 2002; Ebert and Whittenburg, 2006; Bowling et al., 2008), this article contributes an up-to-date consideration of cattle identification methods. This article offers a future vision of animal biometrics traits. In this present study, cattle, beef animals, dairy animals, and livestock are four interchangeable terms.

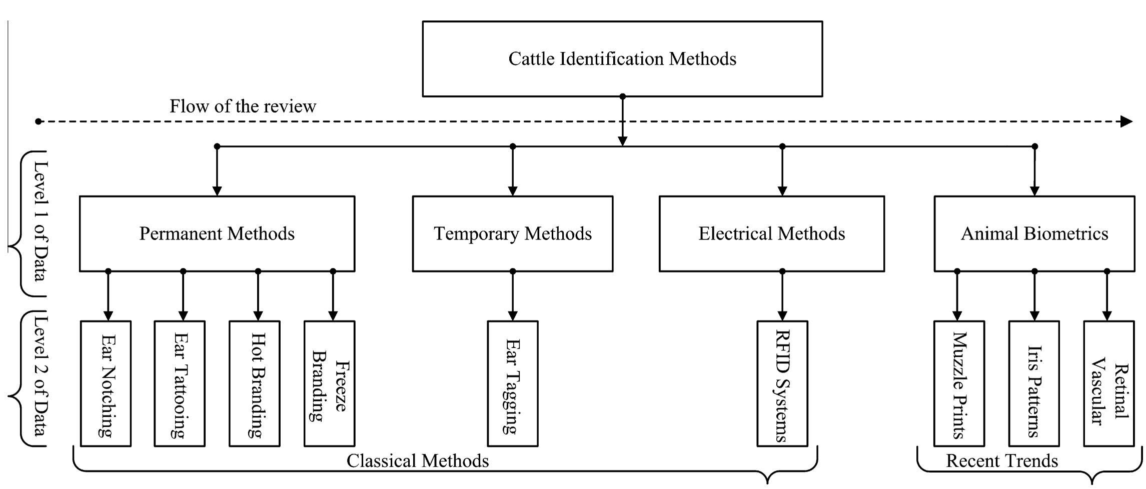


Fig. 1. The flow of the article with respect to classical and recent cattle identification methods, with two levels of data. Level 1 is used for the coarse categorization of cattle identification methods, while level 2 provides detailed descriptions of each identification method.

Fig. 1 illustrates the flow of this article with respect to classical and modern cattle identification methods. Two levels of information are provided: level 1 offers coarse classification information, while level 2 provides a finer classification and deeper descriptions of each identification method.

The article is structured in five sections. Section 2 describes classical cattle identification methods, emphasizing their performance and drawbacks. Section 3 sheds light on biometrics technology, and presents an overview of biometric-based identification systems. Section 3 covers cattle biometrics with respect to muzzle print images, iris patterns, and retinal vascular patterns. Section 4 discusses issues related to classical identification methods, as well as current challenges confront biometric technologies towards developing reliable cattle identification. Finally, conclusions and future research directions are documented in Section 5.

2. Classical cattle identification methods

A fundamental factor in any accurate and effective cattle identification and tracking system is finding a measurable, collectable, distinctive, harmless, and time-immutable identifier for each beef animal. In addition, critical considerations for a secure beef animal identification system include the efficient, reliable, and accurate acquisition of information in a manner that prevents fraud and allows for easy data storage and retrieval. In short, there is evidence of a global need for a safe and efficient system of identifying beef animals (Marchant, 2002; Barry, 2008). Classical identification methods have wide deployments, long time utilization, and documented research investigations. On the other hand, modern biometric-based methods require further research before large-scale applications.

Classical cattle identification systems are grouped into three categories: permanent methods, temporary methods, and electrical methods (Ebert and Whittenburg, 2006). The common problems with these methods stem from their vulnerability to losses, deformations, and fraud, not to mention animal-welfare concerns (Huhtala et al., 2007; Bowling et al., 2008). This section covers each of the three categories.

2.1. Permanent methods

Ear notching is the process of removing a V-shaped section of the right and left ear of an animal; the position of the notch indicates the animal's identity. This approach uses a combination of right-ear notching (litter number) and left-ear notching (animal's number) to uniquely identify each animal. For example, an animal identified as 18-2 is considered as the second animal in a group of 18. This animal would be marked by two notches each at the position 9 on the right ear and two notches at the position 1 on the left ear (Neary and Yager, 2002). Fig. 2(a) illustrates the outcomes of the ear notching operation and the marked locations on the left and the right ear of an animal.

Ear notching can distress a beef animal, and such significant pain should be avoided or reduced via various methods regardless of the potential benefit to the animal or humans (Noonan et al., 1994; Leslie et al., 2010). Ear notching is not scalable and can identify only a limited number of cattle in a manual manner. Thus, it is not a suitable method for medium and large sized farms.

Ear tattooing is another method that is widely used in traditional cattle identification. The ear tattooing marks can be letters, numbers, or a combination of both. A special tattoo pliers is used to place tattoo holes inside the animal's ear, and then an indelible ink is decanted into the holes, where it is trapped under the skin's surface and shows up as letters or numbers (Ebert and Whittenburg, 2006). Fig. 2(b) shows a sample of ear tattooing. This method avoids the problem of distress to the animal, but it is highly susceptible to alteration, duplication, and removal. In addition, ear tattooing has limited scalability. An exhausting, time-consuming, and laborious operation is needed to check, read, and record tattoos in real-time cattle identification.

Hot iron branding uses a farm's brand, letters or numbers, to visually identify beef animals. The brand bearing identifier is heated to a suitable temperature, firmly placed on the animal's skin, and removed immediately. This method should be conducted with special care to the temperature of the branding tool (Ebert and Whittenburg, 2006). Although hot iron branding seems to be a simple identification method, it does not provide enough accuracy or reliability as it can be easily duplicated, removed, or altered. Hot iron branding is prohibited in the UK due to animal-welfare concerns (Stanford et al., 2001).

Freeze branding works differently to the hot branding method; it depends on destroying the natural pigment in the animal's hair. This operation produces white-hair growth in the area of skin the iron touches (Ebert and Whittenburg, 2006). Although this method is simple, its disadvantage lies in its lack of applicability to white animals. Moreover, such brands can be temporarily obscured by changing the white color of the brand to blend with the animal's original color.

Ear tattooing and iron branding are not permanent methods as they can be altered or removed over time. As such, these methods are not time-immutable, and can be naturally deformed as an animal ages. The iron branding method is used for identifying an animal's ownership rather than of the animal's identity, which is not useful in future monitoring and tracking processes.

2.2. Temporary methods

Ear tagging is one of the most widely accepted cattle identification methods. It provides convenient and low cost identification, and it overcomes some problems associated with conventional

(a) (b) (c)

Fig. 2. The foremost classical beef animal identification methods: (a) Ear notching. (b) Ear tattooing. (c) Ear tag with Radio Frequency Identification (RFID) sensor. It is worth noting that these methods are also employed for goats, sheep and pigs. The images were extracted from Neary and Yager (2002) in (a), from Ebert and Whittenburg (2006) in (b), and from web resources in (c).

methods, such as distress to the animal and difficulties pertaining to visual inspection by humans (Barron et al., 2009). Ear tags can be constructed from metal or plastic components and can be labeled with bar codes, numbers, or colors. They may even carry wireless chips for electrical identification systems. The design considerations of any ear tag should render the item tamper-proof and visually legible, and the tag should remain attached without harming the animal (Stanford et al., 2001). Fig. 2(c) shows an example of an animal ear tag.

Ear tags have been found to be susceptible to damages, duplications, losses, unreadability, and fraud. Moreover, ear tags alone do not perform well as a long-term identification method (Fosgate et al., 2006). Metal ear clips may increase an animal's chance of infection, which was the reason for removing 10% of metal ear clips in a study involving 500 sheep in Scotland (Hosie, 1995). These problems led to the development of an electrical identification and registration system. However, the tag itself must be subjected to an electrical transducer; the animal is then identified according to the presence or absence of the ear tag (Wardrope, 1995; Johnston and Edwards, 1996; Barron et al., 2009). Research findings in Fosgate et al. (2006) concluded that ear tags are insufficient for long-term identification because they may be easily lost; only 21% of in-field animals were identified after two years of study. The loss rate was measured as 0.0024 lost tags per day.

Permanent and temporary methods, except ear tattooing, can cause an Unbounded Cost (UC) as an additional cost that may appear after applying the identification method. The UC is connected to the unexpected consequences such as infections or skin diseases that may occur. According to a study on dairy goats by Carné et al. (Carné et al., 2009), the utilization of electronic ear tags led to three cases (3.3%) where a little bleeding was recorded; three cases (3.3%) showed the presence of infection; and six cases (6.5%) had a marked ear tissue reaction. Additional costs for antibiotics or a veterinarian will be demanded to cure these consequences. Another concern, from the cost perspective, is the difficulty in predicting the required UC budget.

Concerning the ease of deployment and maintenance, permanent and temporary methods share almost all the same characteristics. Both need special tools for installation and removal, and the incorrect utilization of those tools may harm the operator or the animal, especially in the branding and tattooing methods. Ear tags, in contrast, can be removed with little pain to the animal. Permanent and temporary methods do not allow for any automatic data recording; rather, all cattle need to be manually identified, thus requiring significant labor (Geers, 1994). However, machine vision techniques have recently been developed for automatic ear tag reading, but so far only in a controlled environment (Velez et al., 2013).

2.3. Electrical methods

RFID technology uses radio waves for human or object identification. It is considered as an appropriate technique in a wide range of industries and applications, including agriculture, access control, supply-chain tracking, vehicle parking and tracking, library books tracking, and smart shopping systems (Ruiz-Garcia and Lunadei, 2011; Roberts, 2006). A generic RFID system consists mainly of RFID tags (transponders), an RFID reader, and a management host or server. The generic structure of an RFID system for cattle tracking is shown in Fig. 3.

RFID tags can be grouped by utilization purposes, operating frequency, and technology. From the utilization standpoint, RFID tags can be grouped into boluses, ear tags, and injectable glass tags (Voulodimos et al., 2010). Klindtworth et al. (1999) reported that injectable transponders have reached a high level of reliability and security. However, further research is needed regarding transponder recovery from the food supply-chain and sensor integration. Carné et al. (2009) argued that electronic ear tags are the most efficient devices because their readability values are greater than those of injectable transponders. A comprehensive review of the readability of 13 different RFID ear tags is presented in Wallace et al. (2008).

From the operating-frequency perspective, RFID tags can be grouped into low-frequency (LF) (125.0–134.5 kHz) and high-frequency (HF) (13.56 MHz) devices. The LF band has been assigned to animal identification (Voulodimos et al., 2010; Ruiz-Garcia and Lunadei, 2011). From the technological viewpoint, RFID tags can be categorized as active tags, which emit radio waves, or passive tags, which do not. Active tags operate at high frequencies (455 MHz, 2.45 GHz, or 5.80 GHz) and offer a reading range of 20–100 m, whereas passive tags operate at lower frequencies (124 kHz to 960 MHz) and offer a reading range of 0.33–3.30 m (Trevarthen, 2007). RFID systems have been selected for cattle tracking because they offer non-contact object tracking, can be easily managed remotely, and can be scaled up or down by adding or removing tags with small configuration efforts.

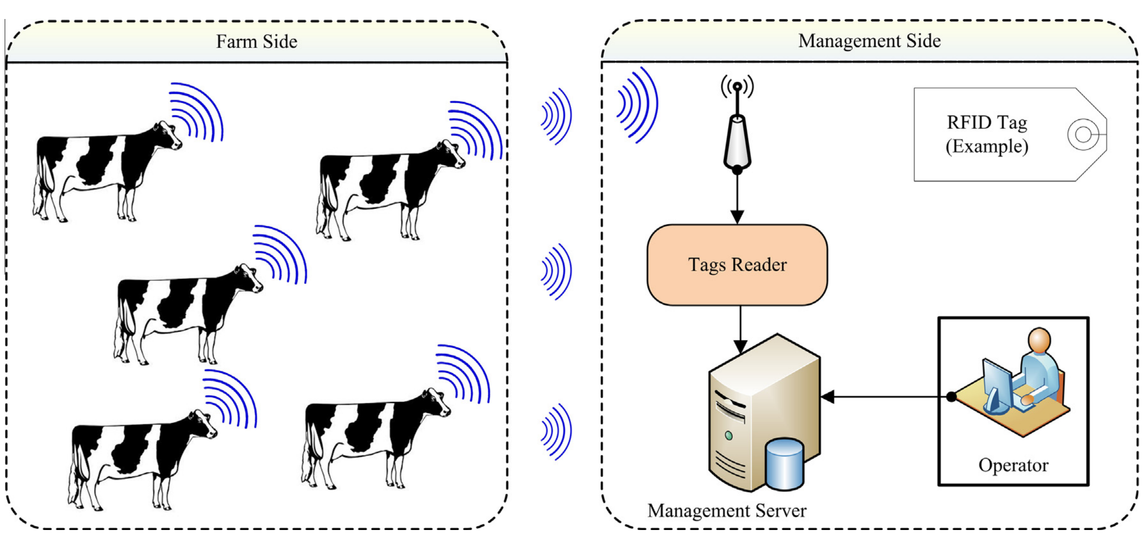


Fig. 3. The common architecture of the RFID system for beef animal identification. The figure sketches the RFID tags in a farm side, a tag reader, and the location of the management server. The tag reader can be handheld or stationary.

Table 1
A comparison of classical cattle identification methods. The ● symbol means high, the ◑ symbol means intermediate, and the ○ symbol means moderate. The □ symbol means low. The (–) symbol means not available (Stanford et al., 2001).

Method	Cattle related		Marker related					Operability	
	LoP	PoFC	EtR	SoR	PoF	DT	AFF	EoA	SS
Permeant methods									
Ear notching	○	–	◑	◑	◑	□	●	○	□
Ear tattooing	○	–	○	○	◑	□	●	□	□
Hot branding	□	–	○	●	◑	□	●	○	□
Freeze branding	●	–	○	○	◑	□	◑	○	□
Temporary methods									
Plastic dangle	●	●	◑	○	□	□	●	●	○
Plastic bar code	●	●	□	○	□	□	○	●	○
Metal ear clip	◑	●	○	◑	□	□	●	●	○
Electrical methods									
Injectable RFID	◑	○	●	◑	◑	●	○	◑	◑
Collar RFID	●	●	●	◑	□	●	●	●	◑

Although RFID systems overcome some limitations of the traditional identification approaches, they present several security drawbacks that are distributed over the entire RFID system (RFID tags, communication channel, tag reader, RFID network, and the RFID back end). The identified security drawbacks include tag-content changes, a high possibility of system spoofing, and Denial-of-Service (DoS) attacks (Roberts, 2006; Rotter, 2008). The main disadvantage of using RFID-based systems for animal identification is that RFID modules require efforts and labor work in order to be configured as an identification and tracking system. The cost of purchasing and replacing RFID tags, in addition to the cost of operating the identification system, should be taken into consideration.

Comparing RFID and other classical identification methods has highlighted a number of advantages of the former. RFID tags can hold relatively large amounts of data that assign a unique code to every tag. Thus, a single tag can track an animal from birth to slaughter. Given the possibility of data storage, an RFID tag can host further information about the tracked animal, such as age, sex, breed, and color. Furthermore, it can host information about the owner, the farm, diseases, and the animal's vaccination status. RFID systems can interact with other animal data recording systems for improved credibility and usability (Samad et al., 2010), and can also be integrated with mobile computing for enhanced accessibility, scalability, and performance (Voulodimos et al., 2010).

The comparison criteria applied to all classical methods, including electrical RFID, involve factors that pertain to the cattle, to the marker, or to the overall system's operability. Cattle-related factors are Lack of Pain (LoP) and Protection from entry into the Food Chain (PoFC). Marker-related factors are Ease to Read (EtR), Success of Reading (SoR), Protection from Fraud (PoF), Data Transfer (DT), and Affordability (AFF). System operability-related factors include Ease of Application (EoA) and System's Scalability (SS).

The former comparison criteria span all RFID system's components. Ease to Read (EtR) represents how easy it is to read the tag or marker, while SoR represents how reliably a tag can be read without error. An RFID system does not depend on line-of-sight technology; it reduces the reading error from 6% (observed for the classical approaches) to 0.1% (Eradus and Jansen, 1999; Ruiz-Garcia and Lunadei, 2011). Identification time, the time spent for correctly identifying an animal, correlates with the Data Transfer (DT). An RFID system can read up to 1000 tags per second, while the process consumes up to 10 s per animal in case of ear tags (Stanford et al., 2001; Ruiz-Garcia and Lunadei, 2011). System's Scalability (SS) represents the possibility of expanding the identification system without changing it altogether. Protection from Fraud (PoF) or circumvention represents the system's ability to defend against any external attack. Table 1 shows an extended comparison of classical cattle identification methods.

The required cost is another comparison factor of classical identification methods. A Predicted Cost (PrC) parameter is introduced which represents the required cost level of each classical method. The PrC parameter is extracted by assessing the PoF, AFF, EoA, and SS parameters from Table 1. These four parameters were selected due to their impact to the method's overall cost. The UC pertaining

Table 2
An estimation of the Predicted Cost (PrC) level of classical cattle identification methods. The ● symbol means high, the ◑ symbol means intermediate, the ○ symbol means moderate, and the □ symbol means low. The (–) symbols means not applicable.

Method	Marker related		Operability		Unbounded	Longevity	Predicted
	PoF	AFF	EoA	SS	Cost (UC)	LoN	Cost (PrC)
Permeant methods							
Ear notching	◑	●	○	□	●	●	●
Ear tattooing	◑	●	□	□	□	●	◑
Hot branding	◑	●	○	□	●	●	●
Freeze branding	◑	◑	○	□	○	◑	●
Temporary methods							
Plastic dangle	□	●	●	○	□	□	○
Plastic bar code	□	○	●	○	□	□	◑
Metal ear clip	□	●	●	○	○	□	◑
Electrical methods							
Injectable RFID	◑	○	◑	◑	○	●	○
Collar RFID	□	●	●	◑	–	◑	□

to permanent and temporary methods is considered. The method's Longevity (LoN) is also considered as a factor in the assessment process. The predicted cost level is inversely proportional to the PoF, AFF, EoA, SS, and LoN levels, while it is a function of UC level. The estimated PrC level of each method is documented in Table 2. The documented PrC level offers a general indication about the cost of every method. However, other factors such as the hardware cost, the installation cost, and the operational cost are not considered in the assessment process, the cost of these factors varies in both location and time.

From the cost perspective, permanent and temporary identification methods can be easily managed by the farm owner after installation. Thus, most of the planned cost goes to the initial installation phase. This situation is different to the RFID case as it needs a professional person to perform the initial installation, and it also requires continuous system operation and management. This, of course, imposes a new human-related security concern. Moreover, the training cost for the farm owner should be counted if one would like to take control of the management of the RFID-based identification system.

Identifying the most appropriate identification method from the list of classical methods is not an easy task. It involves the farm size on top of the evaluation factors in Table 1 and the predicted cost in Table 2. On small farms, the deployment cost is a major concern when selecting an identification method (large-scale identification is not needed on such farms due to the limited number of animals). On large farms, the deployment cost can be outweighed by the benefits of an RFID system, which not only provides cattle identification but also lends support in legal situations and safety inspections. Many researchers encourage reducing tag costs, improving tag readability, and enhancing a tag's overall processing capability. In addition to the suggested tag improvements, RFID security, privacy, and operational challenges should be taken into consideration (Ruiz-Garcia and Lunadei, 2011).

3. Animal biometrics

3.1. Biometrics science

The term biometrics comes from the two Greek roots: bio, which means "life" and metrikos, which means "related to measurement". It is well known that humans intuitively use some bodily characteristics, such as face, voice, and gait to recognize each other (Jain et al., 2004, 2011). Biometrics technology is a key fundamental security mechanism that assigns a unique identity to an individual according to some physiological or behavioral features (Jain et al., 2004, 2011; Giot et al., 2013; Nigam et al., 2015). These features are sometimes called biometric modalities, identifiers, traits, or characteristics. The data reported in Most (2007) and Unar et al. (2014) represents the amount of expected investment in biometrics technology by 2015 as more than 9.9 billion US dollars, and it is anticipated that the total revenue will hit 20.0 billion US dollars by 2018. In this research, the term "biometrics" represents the entire identification system, while the term "biometric" represents a single biometric identifier.

Biometric modalities provide high security while preserving accuracy and reliability by automating the authentication and identification systems. Biometric-based systems avoid some weaknesses of traditional token- and knowledge-based authentication approaches by replacing "something you possess" or "something you know" with "something you are" (Ratha et al., 2001; Goudelis et al., 2008; Lee et al., 2013). Biometrics technology offers not only an automatic authentication method, but also convenience to the user, who does not need to remember information or possess a token (Li, 2006; Schouten and Jacobs, 2009). Driven by its merits, biometrics technology has fueled extensive industrial revenue and investments, and it is becoming fundamental to personal, mobile, and government applications (Most, 2007; Schouten and Jacobs, 2009; Lowrence, 2014; Jillela and Ross, 2015).

A qualified biometric trait must be investigated and filtered through selection criteria. The candidate biometric identifiers should achieve some technical and operational requirements, depending on the type of application. The competency requirements can be summarized as follows: **Universality**, whereby the selected identifier must be available to everyone, and it must be quantitatively measurable without affecting the user's privacy or health; **Uniqueness**, whereby the selected identifier should contain enough features to differentiate between two persons carrying the same trait; **Performance**, that is, the achievable identification criteria (e.g., accuracy, speed, and robustness) and the resources required to achieve an acceptable identification performance; and **Circumvention**, an important parameter that affects the system's reliability, which refers to how easily the system is fooled by fraudulent techniques (Luis-Garcia et al., 2003; Jain et al., 2005; Maltoni et al., 2009; Unar et al., 2014).

Research presented in Jain et al. (2005, 2006) evaluated the performance of individual biometric modalities based on the aforementioned qualification criteria, along with its impact on coupling the suitable identifier with the appropriate application. It is worth noting that no single biometric identifier can achieve excellent performance for all of the requirements listed above (Toledano et al., 2006). Therefore, two or more traits can be fused to achieve greater security (Islam et al., 2013; Tresadern et al., 2013; Yang et al., 2013).

Biometrics technology offers two modes of operation, or two types of applications, namely, identification and verification. Identification is the process of determining the identity of an individual. It compares the presented biometric sample with all previously collected and stored samples in a database, which needs (1:N) matching operations. Verification is the process of confirming the correctness of the claimed identity of an individual. It compares the claimed identity with one or more previously collected and stored samples, which requires (1:1) matching operations (Maltoni et al., 2009; Dunstone and Yager, 2008). In the case of livestock, only the identification mode is considered.

A generic biometrics system is susceptible to different security concerns, such as database compromise, communications interception, and spoofed biometric sample utilization. However, different research directions, such as biometric cryptosystems, cancelable biometrics, and liveness detection techniques are used to address the security concerns in biometrics systems (Rathgeb and Uhl, 2011; Gragnaniello et al., 2015).

3.2. Biometrics system evaluation

Automated Biometrics Identification Systems (ABISs) have replaced human experts in human recognition by applying a computerized approach. An ABIS consists of two phases: enrollment and identification. The enrollment phase registers the individual identity in a database for future use, although assignment of an individual's identity takes place in the identification phase through the matching step, and through user-presented biometric samples (Jain and Nandakumar, 2012).

Fig. 4 shows a generic architecture of an ABIS system for animals. The generic animal biometrics identification system works in the same way as the human biometrics identification system. In the enrollment phase, a biometric identifier is presented, and a feature vector is constructed. Then the extracted feature vector is further manipulated and stored as a biometric template in the database. The identification phase consists of the same enrollment procedure, with additional matching and decision steps. A signal

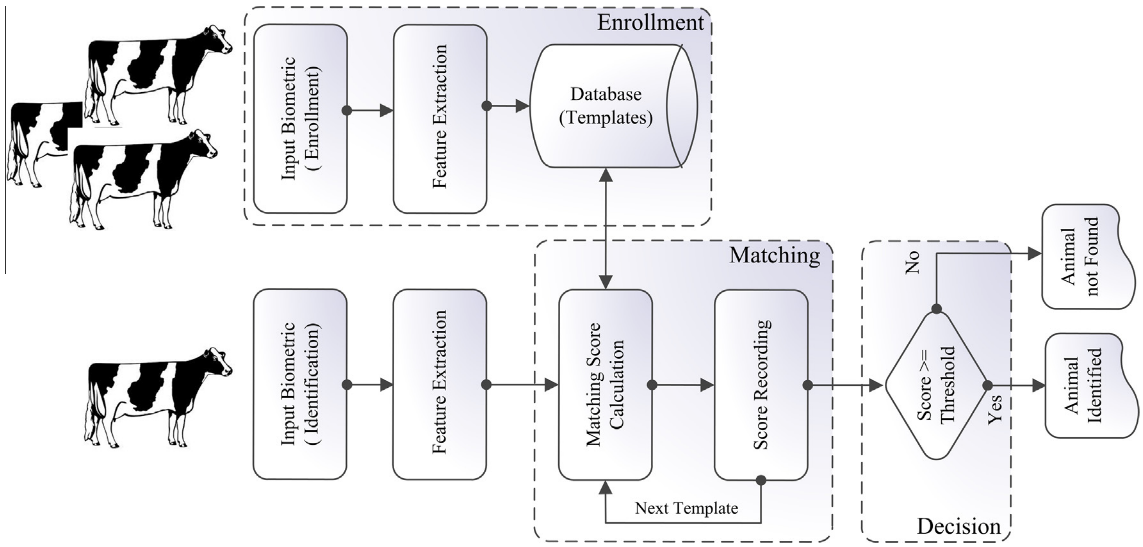


Fig. 4. A block diagram of a complete biometric-based animal identification system (very similar to one used to identify people). The components of the enrollment phase and the identification phase are emphasized in the block diagram (Awad et al., 2013a).

processing point of view provides a deeper look into the ABIS components, including identifier sensing, transmission to the processing machine, identifier processing, identifier classification, matching, and storage (Luis-Garcia et al., 2003).

An ABIS can suffer from several errors that deteriorate the system's performance. These errors can occur at the sensor level, the sample processing phase, the feature extraction phase, or the matching phase. Failure-to-Detect (FtD) error is a sensor error that occurs when a biometric sample is presented to the sensor, but the sensor fails to detect it owing to a hardware problem. The situation is a Failure-to-Capture (FtC) error if the sensor succeeds in detecting a biometric sample, but fails to capture it owing to bad user behavior. A noisy biometric sample leads to a failure in feature extraction, and hence, a Failure-to-Process (FtP) error. These three error types can be combined into one major error class that is called a Failure-to-Acquire (FtA) error. Failure-to-Enroll (FtE) represents the proportion of users that cannot be successfully enrolled in the system due to a failure of template creation (Maltoni et al., 2009; Schouten and Jacobs, 2009; Awad and Hassanien, 2014).

The behavior of the system matcher has a high impact on the system's performance. The matcher can produce two types of errors, the result of inter-user similarity or intra-user variations (Jain et al., 2011). These two errors are called the False Match Rate (FMR) and False Non-Match Rate (FNMR). Some alternative error terminologies can be found in the literature, including the False Acceptance Rate (FAR) and the False Rejection Rate (FRR), for FMR and FNMR, respectively. FAR and FRR are common notions for measuring the performance of a verification system (Schouten and Jacobs, 2009; Maltoni et al., 2009; Unar et al., 2014).

The evaluation of any biometrics system is grouped into three categories: technology evaluation, scenario evaluation, and operational evaluation (Cappelli et al., 2006). Technology evaluation is a repeatable operation that targets specific parts (steps) of the biometrics system, and it uses previously collected biometric data (or databases). Scenario evaluation measures the performance of the entire biometrics system for a particular application in a controlled environment. Operational evaluation is similar to the scenario case, but it is conducted at the actual site of operation (Maltoni et al., 2009; Dunstone and Yager, 2008).

In order to mathematically estimate the FMR, FNMR, and EER, suppose one biometric template is denoted by T, and one presented sample (input) is denoted by I. The similarity score s between the template and the input is measured by the function $S(I, T)$. The hard decision is made according to a similarity threshold h (Awad and Hassanien, 2014).

FMR is the rate that at which the decision is made as I matches T, while in fact I and T come from two different individuals. This means that the biometrics system accepts what should be rejected.

$$\mathrm{FMR}(h) = 1 - \int_{s=h}^{\infty} \mathrm{p}_n(s)\, \mathrm{d}s \tag{1}$$

where $\mathrm{p}_n(s)$ is the non-match distribution between two samples as a function of s.

FNMR is the rate at which the decision is made as I does not match T, while in fact I and T originate from the same individual. This means that the biometrics system rejects what should be accepted.

$$\mathrm{FNMR}(h) = 1 - \int_{s=-\infty}^{h} \mathrm{p}_m(s)\, \mathrm{d}s \tag{2}$$

where $\mathrm{p}_m(s)$ is the match distribution between two samples as a function of s.

The Equal Error Rate (EER) is defined as the value of FMR and FNMR at the point of the threshold (h) where the two error rates are identical ($h = EE$) (Maltoni et al., 2009; Schouten and Jacobs, 2009; Egawa et al., 2012).

$$\mathrm{EER} = \mathrm{FMR}_{h=EE} = \mathrm{FNMR}_{h=EE}. \tag{3}$$

The similarity threshold (h) should be chosen carefully in the system design phase according to the security level and the system's sensitivity. The similarity threshold should achieve a trade-off between FMR and FNMR errors (Awad and Hassanien, 2014). FMR and FNMR are not objective measurements because they are influenced by the selected threshold emerging from the system's application. However, FMR and FNMR are still possible to be used to measure performances of specific systems. The value of EER can be used as a good indicator for measuring the system's performance, and can be selected though the Receiver Operating Curve (ROC) or the Detection Error Trade-off (DET) curve (Maltoni et al., 2009; Noviyanto and Arymurthy, 2013).

The matching module in a biometrics identification mode, with (1:N) matching operations, produces two types of errors, namely the False Negative Identification-error Rate (FNIR) and the False Positive Identification-error Rate (FPIR). The FNIR and FPIR can be computed in the same way as the FMR and FNMR, and they can be extracted from the FMR and FNMR via some simplifications

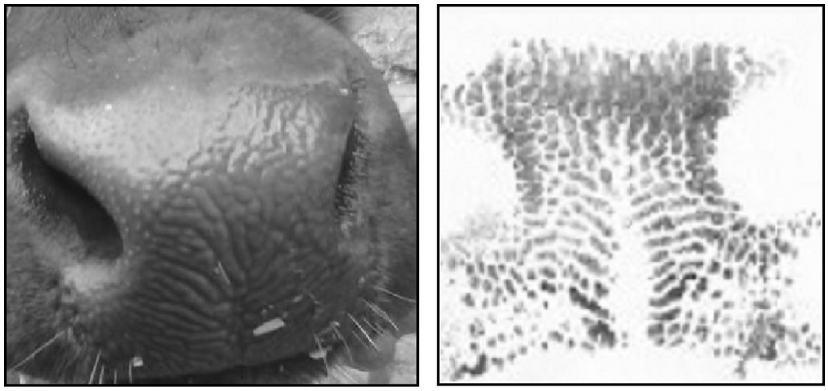


Fig. 5. A sample of muzzle print images of two beef animals: (a) Live-captured (digitized) muzzle print image. (b) Ink-based captured muzzle print image. Both images show the ridges and groove that are the distinctive features of a muzzle print. The image in (b) was extracted from Noviyanto and Arymurthy (2013).

(Maltoni et al., 2009; Dunstone and Yager, 2008). The size of the evaluation database, the distribution of the biometric samples inside the database, and the matcher are involved factors related to measuring the identification performance.

3.3. Cattle biometric identifiers

A common problem with conventional cattle identification systems is that they all depend on devices attached to the animal and not on the animal itself. Biometric identifiers, such as muzzle prints and retinal imaging, offer a rapid and secure method for providing a failsafe animal identification system to ensure the traceability of animals back to the farm of origin (Marchant, 2002; Bowling et al., 2008). On the other hand, animal biometrics face great challenges with respect to collectability and accuracy, and as such it is considered as a research field still in development.

Human biometric identifiers bear some operational and behavioral characteristics, among them are the uniqueness, universality, and performance. Mapping human biometric traits onto animals is a promising technology for animal identification, and it has wide applications that encompass animal classification, animal tracking from birth to the end of the food chain, and understanding animal disease trajectories and animal population patterns. An animal's biometric identifier is permanent, time-immutable, and cannot be easily forged or altered. Therefore, it is less prone to error and fraud; thus in theory, biometrics appears to answer most of the animal identification requirements (Shanahan et al., 2009).

Several animal traits, or identifiers, have been investigated, among them being muzzle print patterns (Barry et al., 2006; Barry et al., 2007), iris patterns, retinal vascular pattern (Barry et al., 2008; Barron et al., 2008; Barry, 2008; Rojas-Olivares et al., 2011), facial image (Corkery et al., 2007), and DNA profiles (Jiménez-Gamero et al., 2006). Each of these can be measured and recorded in a database, providing each animal with a unique identity that remains associated with that animal for life (Barry, 2008; Barron et al., 2009). Moreover, biometrics of animal identification presents an immediate advantage over RFID systems because there is no mass-produced equipment requirement, and biometrics does not require the use of an injected transducer or an affixed ear tag. The following subsections focus on muzzle print images, iris patterns, and retinal vascular patterns.

3.3.1. Muzzle print images

Analogous to human fingerprints, cattle muzzle prints display distinct grooves, or valleys, and beaded structures. These uneven features, distributed over the skin surface of an animal's nose area, are defined by white skin grooves and by black convex areas surrounded by the grooves (Minagawa et al., 2002). An animal's muzzle print can be considered as an accurate and time-immutable biometric identifier, one distinctive enough to identify an animal with an accuracy similar to that achieved by human fingerprints (Baranov et al., 1993). Animals' muzzle prints, or nose prints, have been investigated since 1921 (Petersen, 1922; Minagawa et al., 2002).

Collecting muzzle print images can be achieved via one of two methods: using ink or a digital camera (live-captured images) (Petersen, 1922; Mishra et al., 1995). The former method is conducted by fixing the beef animal's head using a head gate or a halter, and spilling a minimal amount of ink on the animal's dry nose. The ink is transferred to an index card, supported by a wooden block or a similar stiff backing, by pressing the card against the cattle's nose (Neary and Yager, 2002). However, a build-up of moisture on the animal's nose and a failure to hold the animal still can result in smeared, unreadable images. Although this method of identification has proved accurate, the variable amount of time taken to obtain an accurate print is considered a drawback (Barry et al., 2007). Furthermore, the inked muzzle print images are not of sufficient quality to be used in a computerized manner. Fig. 5 shows an example of two muzzle print images captured by a digital camera and by an ink-based method.

Minagawa et al. (2002) used joint pixels of skin grooves as a key feature for muzzle print matching. Some long preprocessing steps were conducted to extract the joint pixels. This approach achieved maximum and minimum matching scores of 60% and 12%, respectively. Among 43 sampled animals from a database of 170, 13 samples were excluded due to a failure in feature extraction. The other 30 animals were all identified against each other, and 20 of the 30 animals were identified against themselves (66.6% total accuracy). The unsatisfactory identification results owed to low-quality muzzle print images, the limited size of the database, and the limited performance of the feature extraction and matching algorithms.

Noviyanto and Arymurthy (2012) applied a Speeded-Up Robust Features (SURF) approach to muzzle print images for cattle identification. A U-SURF method was applied to eight animals, using 15 images each (a total of 120 muzzle print images). The experimental scenario used 10 muzzle-print images in the training phase, and the other five images were used as input samples. The maximum identification accuracy achieved under rotation conditions was 90%.

The lack of a standard and large sized muzzle print database poses a challenge for conducting biometric-based animal identification research. Therefore, compiling a muzzle print image

Fig. 6. A sample of the collected muzzle print images database. The images, from two living animals, show different deteriorating factors: image orientation, blurred images, low-resolution images, and partial images (Awad et al., 2013a,b).

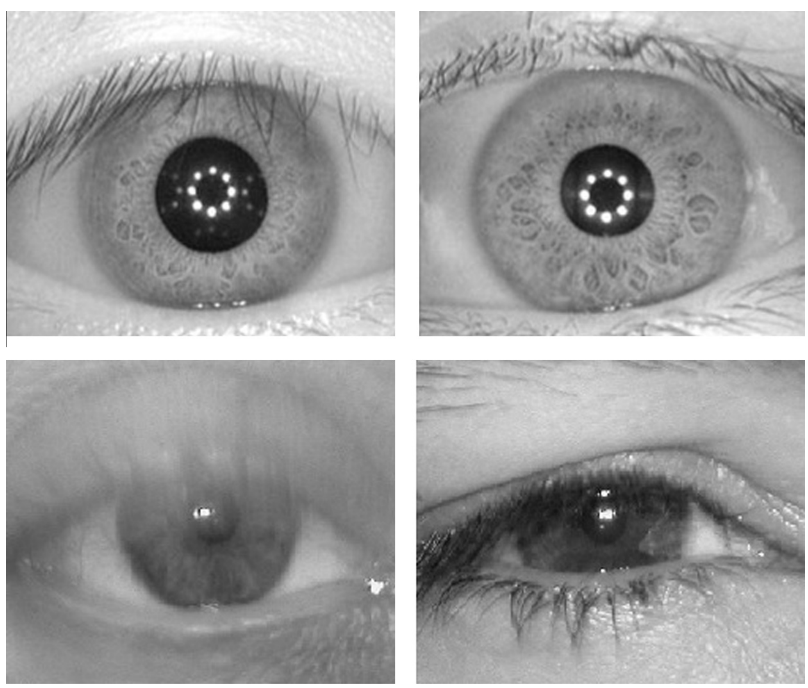


Fig. 7. Normal human iris images taken from the Chinese Academy of Sciences (CASIA) iris database (top row), and problematic iris images, blurred and occluded images, (bottom row) taken from Chen et al. (2013). Similar iris capturing problems may occur when collecting iris images from beef animals.

database is a crucial requirement. The authors in Awad et al. (2013a) compiled a live-captured muzzle print database from 15 beef animals, collecting seven muzzle print images from each (105 muzzle print images in total). The collected images cover different quality levels and degradation factors, such as image rotation and image partiality, in order to simulate real-time identification operations. A sample of muzzle print images from the collected database is shown in Fig. 6.

In Awad et al. (2013b), the authors applied the Scale-Invariant Feature Transform (SIFT) algorithm, combined with a Random Sample Consensus (RANSAC) algorithm, and in doing so they improved the identification accuracy using the previously collected database. Seven images of each animal were swapped between the enrollment phase and the identification phase, and the similarity scores between all of them were calculated to create a similarity score matrix with a dimension of 105×105. The presented approach achieved 93.3% identification accuracy under these conditions with (FMR = 6.6%) on 105 images from 15 cattle animal.

Recently, Noviyanto and Arymurthy (2013) presented a study of using SIFT features and SIFT features combined with a refinement technique for improving identification accuracy.

3.3.2. Iris patterns

Iris pattern is a dominant biometric trait that is applicable to animal identification. The human iris has many distinctive features such as furrows, rings, crypts, and a corona. Daugman (1993) was the first to present an accurate and reliable personal recognition using iris patterns with a 2D Gabor filter (Gabor, 1946) in order to modulate iris phase information and to construct an iris features code. The low user acceptability of iris patterns renders iris capturing a difficult task. User misbehavior creates two main problems: blurred images and images occluded by eyelids or eyelashes (Chen et al., 2013; Juhola et al., 2013). These problems become worse when capturing the irises of animals. Examples of human problematic iris images compared to normal iris images are shown in Fig. 7.

The research in Belcher and Du (2008) presented an iris quality-assessment approach based on the combination of an occlusion score and a dilation score, reflecting two selective iris features. The link between the quality score and recognition accuracy has also been studied in Belcher and Du (2008). A contact-free iris capturing approach may be considered as an affordable solution to the resulted problems arising from animal iris collection operations (He et al., 2008).

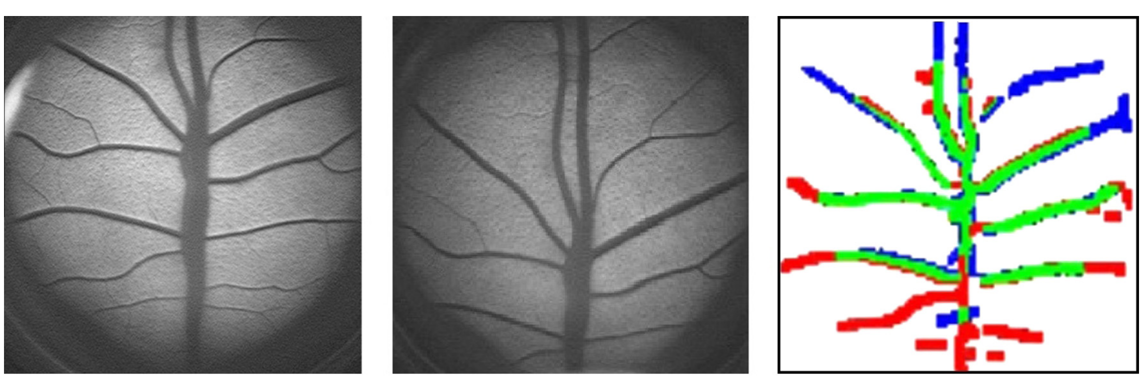
In recent years, the immutability of the iris throughout a person's lifetime has been called into question. Some changes in iris texture appearance may occur with age, disease, and medication, and this can lead to a deterioration or failure of iris-based recognition systems (Rankin et al., 2012). The research in Daugman and Downing (2013) refutes the previous claim by citing the weakness of the evaluation algorithm and a lack of photographic evidence for the texture of an iris to change over time. In a continuation of this scientific sparring, some remarks regarding the refutation in Daugman and Downing (2013) have been presented in Rankin et al. (2013).

The iris of livestock contains some discriminating features, just as the human iris does. In Sun et al. (2013), the authors used SIFT (Lowe, 1999, 2004; Mikolajczyk and Schmid, 2005) as a feature extractor for identifying bovine animals. A local feature of an image is usually associated with a change of an image property, such as intensity, color, and texture (Mikolajczyk and Tuytelaars, 2009). The advantage of using local features in iris identification is that they are computed at multiple points in the image; hence, they are immune to image scale and rotation. In addition, they do not need further iris image preprocessing or iris image segmentation operations (Tuytelaars and Mikolajczyk, 2008). Moreover, the extraction time of SIFT features can be drastically reduced by using modern parallel processing techniques (Awad, 2013).

Recently, the authors in Lu et al. (2014) proposed a cow identification system that incorporates iris patterns with the 2D Complex Wavelet Transform (2D CWT). A contact-free handheld device was used to collect iris images. A database of 60 grayscale images from six eyes with a resolution of 320×240 was compiled. The proposed system achieved an EER of 1.55% in the verification mode, and an overall accuracy of 98.33% in the identification mode. Although the produced results are considered to be high, their confidence is low owing to the database's limited size. It is worth noting that the iris-based identification of cattle faces the same challenges as that of humans.

3.3.3. Retinal vascular patterns

Retinal Vascular Patterns (RVPs) provide considerable cattle identification accuracy; RVPs have features that are similar to human retinal scans. In addition to the high security they provide, RVPs are immutable over time, and the retinal blood-vessel patterns remain essentially unchanged in a normally developed animal eye from birth to maturity (Allen et al., 2008). Retinal patterns can be found in almost all animals, not only beef animals (Barry et al., 2008; Barron et al., 2008; Rojas-Olivares et al., 2011). Therefore, this method can be broadly applied across a wide variety of animals, including goats and sheep. Furthermore, injuries to the eyes cornea do not interfere with the ability to obtain an accurate retinal image (Barry, 2008). The raw retinal image used for enrollment, and the physiological structure of retinal vascular patters are shown Fig. 8.



(a) (b) (c)

Fig. 8. A sample of retinal vascular patterns of a beef animal: (a) Enrolled retinal image. (b) The same image in (a) collected in a subsequent occasion. (c) Extracted and matched retinal vascular patterns from the two images. The reported matching score between the two images is 100%. Images were adopted from Allen et al. (2008).

Table 3
A comparison of biometric identifiers from cattle, identifer, and operability perspectives. The ● symbol means high, the ◑ symbol means intermediate, and the ○ symbol means moderate. The □ symbol means low. The (–) symbol means not available (Stanford et al., 2001).

Method	Cattle related		Identifier related					Operability	
	LoP	PoFC	EtR	SoR	PoF	DT	AFF	EoA	SS
Muzzle print images	●	–	●	●	◑	●	◑	◑	●
Iris patterns	●	–	◑	●	●	●	□	○	●
Retinal vascular patterns	●	–	◑	●	●	●	□	○	●

Like human retinal patterns, cattle retinal vascular patterns are confronted with the same challenges of acceptability, collectability, and processing time (Jain et al., 2005, 2011). The extra challenges that arise in animal identification encompass the difficulty of capturing a retinal image due to eye diseases and a failure to control the animal's movement long enough to accurately capture a retinal image. In Allen et al. (2008), 869 bovine animals were used to capture 1738 retinal patterns (from both eyes), with a maximum achieved identification rate of 98.3%.

Analogous to the comparison of the classical cattle identification methods in Section 2.3, the three discussed biometric identifiers have been assessed from cattle, identifier, and operability perspectives. The outcome of the assessment process is reported in Table 3. The price variations of biometrics system's hardware and software components hinder the assessment of the deployment cost of each cattle biometric identifier.

4. Discussion and future research

Recently, some developing countries have faced food shortages, especially a lack of meat. It is anticipated that this problem will only worsen, given huge population increases (Babu and Sanyal, 2009). Cattle, buffalos and cows, are the major players in the human food chain. Governments have provided vaccinations against most diseases, seeking to overcome some food shortages by keeping cattle as healthy as possible. Cattle identification and tracking have become vital to the food industry for disease control, vaccination management, food-shortage alleviation, and ownership management (Vlad et al., 2012).

The classical cattle identification methods of ear tagging, branding, and tattooing are vulnerable to losses, damages, and fading. Even if tampering is detected, it is difficult to correctly identify the original markings (Dziuk, 2003). RFID identification systems provide dramatic advantages and operational improvements over classical methods, and can lower the reading error in visual detection from 6% to 0.1%. Although RFID seems an appropriate method, it involves many security and privacy challenges that render any such system susceptible to various attacks (Trevarthen, 2007).

Animal biometrics has emerged as a promising cattle identification and tracking mechanism. The three current cattle biometric identifiers are muzzle prints, iris patterns, and retinal vascular patterns. DNA is an additional possibility still under consideration. Fusing two or more biometric identifiers can widen the deployment of biometrics and improve the overall system's accuracy. Although cattle biometrics is in an early phase, it is anticipated that it will attain wide deployment similar to that of human biometrics.

Current cattle biometric identifiers (muzzle prints, iris patterns, and retinal vascular) can be used in the identification and tracking of live cattle until they are slaughtered. This is, of course, useful for taking care of the cattle itself in terms of rearing, vaccination, and disease management, but it is not helpful for tracking meat products. In order to track meat products, extended cattle identification and tracking identifiers such as animal DNA need to receive further research attention.

While muzzle prints, iris patterns, and retinal vascular patterns have received considerable research attention, the challenge of capturing accurate images still exists. Inefficient image capturing leads to low quality and deformed images, which in its turn, produces low identification accuracies. The collectability problem is also considered as an obstacle in front of developing a standard database for every cattle biometric identifier. Therefore, further investigations are encouraged regarding the development of biometric sensors and image capturing facilities for cattle identification.

System operability—how easy it is to install and operate a system—is another dimension that can be used to compare cattle identification methods. In the case of an RFID system, external tags are susceptible to tampering and damage, while internal tags (injected tags) are intrusive and hard to maintain or replace. On the other hand, biometric identifiers are difficult to be collected from uncooperative animals (Lu et al., 2014). Even with quality enhancements, collecting low-quality biometric samples may drastically reduce the overall system accuracy.

RFID systems and animal biometrics compete with each other, and the most appropriate method is selected based on cost, scalability (farm size), ease of installation and operation (system operability), and identification accuracy. In addition, the availability of systems and processes in a given locale should also be taken into consideration.

4.1. Current challenges

Apart from the issues shared with human biometrics, beef animal biometrics is confronted with many additional challenges. These challenges lie in the lack of research frameworks, the lack of standard matching features, and the lack of benchmarks and competitions, which constitute an impediment to progress in the research and implementation of this technology.

Research framework is a collection of algorithms, implementation codes, and hardware platforms for different biometric identifiers. It is an important tool in human biometrics that is also applied in animal biometrics (Chollet et al., 2009).

Databases can be used by various researchers to evaluate their findings; and hence, reported results can be fairly evaluated. Many public databases are available for almost all human biometric identifiers, but there is very little data available for animal identifiers. For example, there are many databases of human fingerprints (Watson and Wilson, 1992; Maio et al., 2002, 2004). In contrast, researchers are left with no alternative but to manually collect and build their own databases of muzzle print images (Awad et al., 2013b; Noviyanto and Arymurthy, 2013). Compiling and standardizing databases of livestock biometric samples (muzzle print images, iris images, and retinal vascular images) is a challenge facing the cattle biometrics research. A standard database can be used for large-scale evaluations of feature extraction, classification, and feature-matching algorithms. A valuable contribution has been made in building a database and releasing a source code for zebra identification (Lahiri et al., 2011), but it is difficult to use this resource for cattle identification purposes.

Standard features have been well-defined for many biometric traits in human biometrics. Minutiae (ridge ending and ridge bifurcation) are the most standard and discriminative features for fingerprint-based identification systems (Maltoni and Cappelli, 2009; Maltoni et al., 2009; Lee and Gaensslen, 2001). Moreover, singular points are also considered as standard and supportive features in different fingerprint processing methods (Gupta and Gupta, 2015). The shortage of standard features in animal identifiers, such as muzzle print images from one side, reduces the commercial applicability of biometrics, and, on the other hand, opens a door for finding different features and applying different algorithms to enhance the performance of biometric-based animal identification systems. Extensive research efforts need to be directed toward extracting standard features from beef animal biometric identifiers for accurate features matching.

Benchmarks and competitions represent another challenge in biometric-based beef animal identification. Because cattle biometrics is still a growing research topic, researchers may not find cutting-edge results with which to compare their findings. Most of the available research related to biometric-based cattle identification reflects individual and limited efforts. Research competitions are sorely needed to encourage researchers to develop algorithms and features and to test various biometric animal identifiers. For each current identifier, standard databases and the best achieved identification accuracy should be available as benchmarks for assisting any future research.

5. Conclusions

Driven by the rapid growth of customer concerns about food safety, and by governmental keenness to increase livestock numbers, a robust and efficient cattle identification system has become a crucial requirement. Classical cattle identification encompasses temporary, permanent, and electrical methods, while modern approaches include the use of animal biometric identifiers such as muzzle prints, iris patterns, and retinal vascular patterns. Cattle identification serves as a basis for further beef animal monitoring and tracking operations. These operations require recording various physical and health characteristics of the animals, in addition to the requirement of basic identification. This article has presented a review of the evolution of cattle identification, from classical methods to recent trends. In addition, it has discussed the current challenges and some future research directions.

Classical temporary and permanent cattle identification methods are not perfect in terms of reliability and accuracy, and problems arise with respect to the cattle, the markers, and the system's operability. Electrical-based identification methods constitute the next generation of approaches: RFID solves several problems present among the classical methods, but it raises many security, privacy, and operational challenges. Selecting the best method from the classical approaches involves various considerations, such as the size of the farm, the cost, and the required functions of the identification process.

Biometrics is a mechanism that assigns a unique identity to a subject using its physiological or behavioral characteristics. Animal biometrics can partially replace the classical identification methods by overcoming their limitations and by fulfilling the requirements for accurate and efficient cattle identification. Although biometric-based cattle identification has received research attention as a promising technology, it has not been deployed on a large-scale basis for reasons including a lack of biometric databases, of feature and algorithm standardization, and of experimental benchmarks. Integrating biometrics technology and the current RFID systems should be pursued in future research as a means of achieving better performance that poses few security challenges.

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