Image-based attributes of multi-modality image quality for contactless biometric samples

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Abstract—The quality of a biometric sample is one of the main criteria having a direct influence on the overall performance of a biometric system. There are many existing researches focusing on biometric sample quality assessment, but different evaluation approaches measure different quality attributes and most of them focus on measuring modality-based attributes. Meanwhile, different biometric modalities seem to be isolated from each other in the image quality evaluation process. Quality metrics that can evaluate multi-modality biometric sample quality is rarely considered. The link of sample quality evaluation between different modalities can be established by using image-based quality metrics, which are able to assess image-based quality attributes. This could be the solution of developing multi-modality biometric sample quality evaluation approaches especially when the fingerprint acquisition sensor becomes contactless. In order to investigate the common framework of biometric sample quality assessment between contactless fingerprint, face, and iris, we will first review the commonly used image-based quality attributes for three modalities by surveying existing literature. Based on the survey, we identify and categorize these attributes to propose a refined selection of important ones for the assessment of multi-modality biometric sample quality.

I. INTRODUCTION

Generally, a biometric sample is of good quality if it is suitable for personal recognition [1]. The term “quality” is used to describe several different aspects of a biometric sample that contribute to the overall performance of a biometric system. For the purposes of standardization, the recent standardization efforts (ISO/IEC 29794-1 Information technology - Biometric sample quality - Part 1: Framework [2]) have defined terms, and a reference model for distinguishing between these different aspects of quality. Depending on context, three prevalent uses are to subjectively reflect biometric sample quality [2]: the character of a sample, the fidelity of a sample to the source from which it is acquired, and the utility of a sample within a biometric system.

During the past several years, biometric sample quality assessment became a significant issue because of biometric systems’ poor performance on degraded samples. Studies and benchmarks have shown that biometric sample quality have a direct influence on the overall performance of a biometric recognition system [1], [3]. Indeed, using a poor quality biometric sample (fingerprint, face, iris, etc.) in the enrollment phase of the subject, the recognition of the person cannot be ensured with a high level of accuracy. For example, a too dark and / or too fuzzy or too noisy sample image at enrollment may require an extra processing step to be able to identify the sample in the system. This operationally important step has nevertheless received little research compared to the primary feature-extraction and pattern-recognition tasks.

Several techniques have been proposed in literature to assess the quality of a biometric sample that is affected by different degradations. Samples from different modalities usually have their own modality-specific degradation (e.g. scars in a fingerprint image or eyes closed in a face image) so that the most common way to measure sample quality is to use modality-based image quality metrics. However, quality metrics that can evaluate multi-modality biometric sample quality is rarely considered [4]. The link of sample quality evaluation between different modalities can be established by using image-based quality metrics, which are able to assess image-based quality attributes (illuminant, sharpness etc.) [4]. This could be the solution of developing multi-modality biometric sample quality evaluation approaches especially when the fingerprint acquisition sensor becomes contactless (e.g. smartphone based fingerprint).

It has been proven that image-based factors can influence biometric systems performance [5], but, so far, there is no agreement on which image-based quality attributes are the most important. In order to overcome the challenges mentioned above, the main objective of this paper is to propose a selection and classification of image-based attributes for the assessment of multi-modality biometric sample quality. First, we will review and investigate the common image-based attributes that have been measured in fingerprint, face, and iris modalities. Then identify and categorize them to propose a refined selection of important attributes for the assessment of biometric sample quality. These image-based attributes can be used to create a link between fingerprint, face, and iris or even more modalities’ sample quality evaluation. The identification and categorization of image-based attributes can be used to assist in the assessment of multi-modality biometric sample quality and to improve or develop new evaluation methods for more than one biometric modality. As fingerprint modality can be separated into two categories: contact-based (touch-based) sample and contactless-based sample. Due to contactless-based fingerprint having more similarities with face and iris compared to contact-based fingerprint, this paper mainly focus on contactless-based fingerprint samples.

In order to have a better overview of the research topic in-
In this paper, an established common framework of image-based multi-modality biometric image quality assessment is illustrated in Figure 1. The contribution of this paper is shown in the blue dashed line rectangle. Investigation and selection of common image-based attributes is the first and a very important stage of this framework. Based on the selected image-based attributes, image quality metrics (IQMs) have been used in different modalities for these common attributes could be selected and optimized in the next stages. Finally, a multi-modality image-based biometric sample quality index can be developed by fusing optimized IQMs.

This paper is organized as follows. Section II is a survey of image-based quality attributes that have been measured in existing literature. Section III discusses the selection and definition of important image-based attributes for the assessment of multi-modality biometric sample quality. The last Section concludes the discussion and suggests directions for further research in this field.

II. STATE-OF-THE-ART

Based on previous research [1], [6]–[9] and biometric sample quality standards [2], [10]–[12], there are many quality attributes that affect biometric sample quality for fingerprints, face, and iris. Some of these attributes can be classified as modality-based attributes, which means that such attributes could only affect the sample quality in one specific modality. Other attributes can be categorized as image-based attributes affecting biometric sample quality in more than one modality. A brief survey of image-based quality attributes have been investigated or measured in existing literature is presented in this section.

A. Image-based Attributes Influencing Contactless-based Fingerprint Image Quality

High quality fingerprint samples will result in high recognition performance, but it is not easy to capture high quality sample constantly during the acquisition process. Song et al. [13] proposed a new scheme for contactless-based fingerprint recognition system. They found out that the system raises some problems, such as: motion blur, CCD background noise, non-uniform lighting, and low ridge-valley contrast. Lee et al. [14] presented an image pre-processing method for fingerprint images captured with a mobile camera. In their method they stated that weak fingerprint contrast and image noise are two of main factors that lead to poor sample quality. In a study of contactless fingerprint recognition system [15], it was pointed out that there are some disadvantages in the system, for example, low contrast between the ridges and valleys, background noise, and motion blur. Hiew et al. [16] concluded that the problems of the contactless-based fingerprint recognition are the low contrast between the ridges and the valleys, defocus, and motion blur. Piuri and Scotti [17] found out that defocusing, motion blur, and noise of CCD are common application problems in contactless-based fingerprint biometrics. Labati et al. [18] proposed a quality measurement of fingerprint images in contactless biometric systems. In their approach they assessed more than 45 quality factors, for example, image focus, illumination, image contrast, noise, blurring effects and so on. Han et al. [19] compared contactless-based fingerprint images with touch-based images. The findings showed that low contrast between the ridges and valleys and illumination problem can affect fingerprint image quality. A similar research topic from Labati et al. [20] stated that uncontrolled light conditions, poor contrast between ridges and valleys, out of focus, and noise are always present in contactless fingerprint images to decrease sample quality. After studying fingerprint recognition with embedded cameras on mobile phones, Derawi et al. [21] discovered that illumination, clarity, and contrast are the quality attributes that influence fingerprint sample quality in contactless-based system. A paper from Yang et al. [22] assessed contactless-based fingerprint image quality by evaluating a 12-dimensional quality feature including motion blur, de-focusing, unfavored illumination, exposure, and noise.

B. Image-based Attributes Influencing Facial Image Quality

Many different attributes can be considered in facial image quality assessment. Part of them are already stated in associated research papers: Abate et al. [23] conducted a survey of 2D and 3D face recognition. They stated that illumination is one of the key quality attributes that can significantly affects system face recognition performances. Hsu et al. [24] proposed a quality assessment framework to evaluate face sample quality. Several image-based attributes are listed in their research that can affect face sample quality: compression artifacts, exposure, contrast, sharpness, lighting, and color. Gao et al. [25] presented an approach for standardization of facial image quality. In their research, illumination, contrast, and sharpness are image-based attributes influencing facial image quality. Nasrollahi and Moeslund [26] proposed a system based on four simple quality attributes including out-of-plan rotation, sharpness, brightness, and resolution, to assess the face quality in a video sequence. It is obvious that sharpness and brightness are two image-based attributes. Zamani et al. [27] pointed out that quality problems observed such as shadows, hotspots, video artifacts, blurring, salt and pepper noise, and movement blurring are common attributes that affect the face recogni-
tion system performance. Artifacts, sharpness are two image-based attributes can be extracted from their statement. Sang et al. [28] presented several algorithms for face image quality assessment. Illumination and sharpness are two important attributes they suggested to be measured. In ISO/IEC 29794-5 Information technology - Biometric sample quality - Part 5: Face image data [11], a number of image-based attributes are recommended to be evaluated: luminance, artifacts, brightness, contrast, exposure, sharpness, and color.

C. Image-based Attributes Influencing Iris Image Quality

The performance of the iris as biometrics is highly dependent on the quality of the sample. Some major covariates in iris recognition include focus and motion blur, off-angle, occlusion, dilation/constriction, and resolution. In order to compensate for these covariates, early iris capture systems were bulky and cumbersome to use. However, as newer and compact sensors with focus on usability emerge, there is greater need to measure the quality of the captured sample. A brief review of image-based attributes that have been measured in the literature is presented here. In 1996, Williams [29] suggested that an iris recognition system should evaluate quality of image focus to ensure the system performance. Kalka et al. [30] extended previous research efforts on iris quality assessment by analyzing the effect of several image-based attributes: defocus blur, motion blur, and lighting. Wei et al. [31] proposed a novel approach for iris image quality assessment by evaluating two image-based attribute out of three: defocus and motion blur. Belcher and Du [32] showed that many attributes can affect the quality of an iris image, including three image-based attributes: defocus, motion blur, and image contrast. Li et al. [33] developed a novel framework for comprehensive assessment of iris image quality in three aspects. One of the aspects is measuring defocus and motion blur. The recent established ISO/IEC 29794-6 Information technology - Biometric sample quality - Part 5: Iris image data [12] proposed evaluation methods for iris image quality. In this standard, iris-sclera contrast, iris-pupil contrast, grey scale utilization, sharpness, motion blur, and artifacts are recommend to be assessed.

D. Classification of Image-based Attributes

In order to better understand image quality evaluation in biometrics, it is necessary to inspect the different image-based quality attributes that commonly measured in biometric samples. Bharadwaj et al. [4] have classified image-based attributes into four groups:

- Blurring: Image blurring is a common attribute that occurs due to defocus, motion, or certain environmental factors.
- Illumination: Non-uniform lighting is essential for the acquisition of a bad quality biometric sample. In the same words, adversely directed lighting drastically affects the performance of fingerprint, face, and iris recognition.
- Noise/Compression: An image may be introduced noise due to environmental factors, incorrect use of sensors, and transmission errors. Depending on the compression levels, various image encoding techniques produce artifacts.
- Optical distortions: Nonconformity to rectilinear projection causes distortion in the captured images.

Degradations of aforementioned image-based attributes usually occur due to the limitation of sensor technology or the condition of experiments. As the constraints on human beings during acquisition are not well controlled, the impact of these attributes on the performance of biometric systems increased drastically. Consequently, the assessment of these attributes are critical for developing effective and robust biometric systems.

III. INVESTIGATION AND SELECTION OF IMPORTANT IMAGE-BASED QUALITY ATTRIBUTES

The first step in the common framework is to identify the relevant and important image-based attributes. We took the approach of doing a survey of the existing literature. Many attributes have been considered as important and evaluated by researchers to quantify biometric sample quality for fingerprint, face, and iris. These image-based attributes include, motion blur [12], [13], [15]–[17], [27], [30], [31], [33], CCD background noise [13], [17], lighting [13], [20], [24], [30], contrast [11]–[16], [18]–[21], [24], [25], [32], image noise [14], [18], [20], image background noise [15], defocus [16], [17], [20], [30]–[33], image focus [20], [29], illumination [19], [20], [23], [25], [28], blurring effects [20], [27], illuminance [21], clarity [21], compression artifacts [24], exposure [11], [24], sharpness [11], [12], [24]–[28], color [11], [24], brightness [11], [26], salt and pepper noise [27], luminance [11], artifacts [11], [12], gray scale utilization [12]. An overview of commonly used image-based attributes is illustrated in Figure 2.

A. Overall Classification of Image-based Attributes

When reducing these attributes we surveyed, we need to consider several important issues. A long term goal of this research is to create a link between fingerprint, face, and iris sample quality assessment. With this intention, the quality
attributes have to be general enough to be assessed in all three modalities, while they should play an important role in each modality. In addition, the quality attributes have to be suitable for IQMs to address the intended assessment methods. The existing sets of quality attributes do not fulfill all of these requirements, and therefore a new set of quality attributes is needed.

Many of the aforementioned quality attributes are similar and have common denominators, which allows them to be grouped within more general attributes to reduce the dimensionality and create a manageable evaluation of sample quality. Usually a compromise is necessary between generality and accuracy when it comes to dimensionality. A smaller set of general attributes results in lower accuracy but also lower complexity, vice versa [35]. According to the consideration stated above and the aspect of important for the assessment of IQMs, we classify most of the reviewed quality attributes to the following five different dimensions:

1) The **contrast** attribute has two aspects: local contrast and global contrast. The local contrast can be defined as the average difference between neighboring pixels. The global contrast is defined as the weighted sums of the overall local contrast for different resolutions.

2) The **sharpness** attribute is defined as the clarity of biometric sample structure and details.

3) The **luminance** attribute can be defined as the intensity of the biometric sample illumination.

4) The **artifacts** attribute is given as any undesired alteration in biometric sample introduced during its digital processing, such as noise, compression and so on.

5) The **color** attribute is defined as the color information that can be additionally used for biometric recognition in order to improve sample quality and system performance.

We used Venn diagrams to create simple and intuitive illustrations of the image-based attributes and their influence on overall biometric sample quality. Venn diagram can be used to show possible logical relations between these four attributes. Color information is known not to affect current biometric recognition performance of major biometric system [11], but more and more researches start paying attention to use color attribute to improve biometric sample quality and system performance [36]–[38]. Therefore we illustrated the image-based attributes using only four folds, leaving the color attribute out for future research interests. However, a five folds Venn diagram includes color attribute is expected in the future.

The Venn diagram in Figure 3 shows how the overall biometric sample quality affected by one, two, three, or four of the image-based attributes. Some attributes are interdependent [39], addressing image quality to a multidimensional problem [40], in this case four dimensions. The folds in Figure 3 may have different sizes or positions because of these attributes can affect the overall biometric sample quality in different ways. In addition, there is always a trade-off between preserving independence and reducing all of the existing image-based attributes to five dimensions. By taking into account the aspects of biometric sample quality as many as possible, it is not easy to keep the balance.

The aforecited five image-based attributes are a good starting point for the biometric sample quality assessment, especially they can be applied to multiple modalities. Each attribute may have specific meanings in different biometric modalities. Furthermore, these attributes may also have sub-attributes. Such issues will be discussed when we take a closer look at the five different image-based attributes in the following.

**B. Contrast**

While contrast for simple images is well defined, contrast for complex images is not [41]. Real world images and therefore biometric images can be considered as complex images while simple images rather contain test patterns like sinusoidal gratings [11]. Contrast as an image attribute is usually defined as ratio between the brightest and the darkest spot in the image. The human perception of the image contrast does not completely correspond to this definition. Therefore, it is necessary to investigate different contrast definitions.

There are several commonly used definitions for contrast in literature, such as Michelson contrast [42], Weber contrast [43], and band-limited contrast [44]. A recent proposed method for computing contrast, a Global Contrast Factor (GCF) [45]-was recommended by the ISO/IEC 29794-5 standard [11]. This method is based on the local contrast at a given position in its neighborhood. Based on this local contrast, the global contrast is given as the weighted sums of the overall local contrast for different resolutions.

Contrast is clearly difficult to define, and its definition changes according to the application. Considering the property of fingerprint, face, and iris biometric sample images, the definition of our contrast attribute can refer to the definition of local and global contrast proposed in GCF [45].

In order to evaluate the fingerprint image contrast, we need a method for measuring the contrast of ridge-valley structure. According to the definition stated above, the given position \( f(x, y) \) could be a pixel on the ridge and the neighboring
pixels could be the corresponding valley pixels. For face images, we can apply the proposed method to calculate the contrast on the face structure. For iris images, we should not only calculate the contrast for iris structure, but also compute the iris-sclera contrast and iris-pupil contrast. In conclusion, the aforementioned contrast definition is suitable for defining contrast in multiple modalities.

C. Sharpness

We consider sharpness as another important image-based attribute because it has been commonly used in biometric sample quality assessment. Caviedes and Oberti [46] defined sharpness as the clarity of detail and edge in an image. Bouzit and MacDonald [47] also suggested that sharpness should related to details and edges. Fedorovskaya [48] proposed to define sharpness as the overall impression of clarity of edges observed within the entire image. Fingerprint ISO/IEC standard [10] used ridge-valley clarity to represent fingerprint sample sharpness. Face ISO/IEC standard [11] stated that the sharpness of a face image refers to the degree of clarity in both coarse and fine details in the face region. Iris ISO/IEC standard [12] presented a method for iris sharpness by measuring the degree of focus present in a iris sample image. By taking into account all the aspects stated above, we can define our sharpness attributes as the clarity of biometric sample structure and details.

Image-based attributes that are suitable to group within the sharpness attribute are diverse and many, including sharpness [11], [12], [24]–[28], motion blur [12], [13], [15]–[17], [27], [30], [31], [33], defocus [16], [17], [20], [30]–[33], image focus [20], [29], and blurring effects [20], [27].

D. Luminance

A common definition of luminance is the intensity of light emitted from a surface per unit area in a given direction. Here we define luminance as the intensity of the biometric sample illumination. It is important to evaluate whether the biometric sample illumination is too strong or too weak. In addition, whether the intensity of the illumination is uniformed or not also plays an important role in biometric sample quality assessment. Many image-based attributes used by other researchers can be included within our luminance attribute, such as lighting [13], [20], [24], [30], illumination [19], [20], [23], [25], [28], and illumination [21].

E. Artifacts

Many artifacts were discovered by other researchers in biometric samples, for example, noise, compression degradations, etc. There are three sub-attributes can be classified in our artifacts attribute: noise, compression distortions, and optical distortions. The noise in biometric images depends on the different processes that are required to generate a digital image. The introduced noise is particular relate to the sensor or process involved. Relevant noise sources include: 1) digital image acquisition devices (e.g. digital camera); 2) analogue image acquisition devices; 3) image scanning devices; 4) digital transmission errors. Compression artifacts are noticeable distortions of images caused by the application of lossy data compression. It contains several different distortions so it is complex. The majority component in compression artifacts is blocky artifact. The last sub-attribute is optical distortions. Any effect of optical distortion including spherical aberration, chromatic aberration, astigmatism, and coma that an biometric sample image may exhibit should be assessed to ensure that they cause no significant worsening of error performance for the designed configuration. There are a variety of assessment approaches for each artifacts. Therefore we will not discuss any particular method here.

We can link the presented artifacts image-based attribute with several of the attributes used in the literature. For instance, CCD background noise [13], [17], image noise [14], [18], face, image background noise [15], compression artifacts [24], salt and pepper noise [27], and artifacts [11], [12].

F. Color

Even though color information is known not to affect current biometric recognition performance of major biometric systems, but if the color of the background is known, it can be used to calibrate the image (e.g. 18% gray). Furthermore, more and more research start considering the color information in order to improve biometric sample quality [36]–[38]. We believe that color attribute will be an important image-based biometric attribute in the near future.

IV. CONCLUSION AND FUTURE WORKS

The main goal of this paper is to select the most suitable image-based quality attributes for multi-modality contactless biometric sample quality assessment. To determine the most suitable image-based quality attributes, first, a literature survey is indispensable. In this survey, all attributes that affect biometric sample quality for contactless fingerprint, face, and iris are reviewed. In order to discover the relationship between contactless fingerprint, face, and iris sample quality evaluation, after the survey, we introduced a proposed common image-based framework for the multi-modality biometric sample quality assessment and then investigated the most important and commonly measured image-based quality attributes in the literature based on the framework. Finally, the definition of the five most important image-based attributes are given and illustrated in detail.

One of the future work could be the investigation of the color attribute and related research topics. Using color light sources and multispectral acquisition sensors are state-of-the-art. Another further work is to study the possibility of finding image-modality based attributes. By using proposed common framework and selected image-based attributes, image-based metrics that can measure multi-modality contactless biometric samples becomes possible. In addition, the proposed framework and image-based attributes are able to be applied to other biometric modalities, such as palm, gait, and ear etc. This is another one of the interesting research topics could be payed attention in the future.