# DECISION MAKING IN MULTI-BIOMETRIC SYSTEMS BASED ON FUZZY INTEGRALS

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**Annotation.** Use of fuzzy integrals is proposed for aggregation of classifiers results in multi-biometric systems. It is significantly better than application of a single classifier. Also, advantages and disadvantages of application of fuzzy integral method are reviewed.

## 1. Introduction

Biometric authentication methods provide a higher security and convenience for users, than traditional methods such as use of passwords or tokens. For these reasons, security systems are gradually transferring from passwords and keys to biometric methods of verification of authenticity of users. However, biometric systems have different restrictions.

It is known that, some people have poor quality fingerprints, image of face depends on lighting, voice can hoarse due to cold, original image of iris projected on a lense can "deceive" different biometric authentication systems. All these disadvantages can be overcome in multi-biometric systems which combine the results received based on several biometric characteristics independent from each other.

Multi-biometric system includes the combination of different biometric characteristics: fingerprints, iris, keyboard signature, handwritten signature, face image, voice etc. Application of different combinations of biometric data of a person is used where there is a restriction of one biometric feature. Fusion of two or more biometric characteristics provides effectiveness of the biometric system even at the highest requirements for authentication. From reliability point of view, it is difficult to spoof multi-biometric system, as it is difficult to simultaneously create several biometric characteristics.

There are different levels of information fusion in multi-biometric systems:

1) sample level;
2) feature level;
3) score level;
4) decision level.

Majority of works on multi-biometric systems focus on methods of information fusion on the of score level based on speed and effectiveness. There are several known works on application of fusion method on sample level.

Different fusion (aggregation) methods of value relevance are used in multi-biometric systems: neural networks, Bayesian nets, discriminant functions.

Aggregation operators must have behavioral characteristics as well as mathematical properties (boundary conditions, idempotence, continuity, monotonicity (non-decreasing), associativity, symmetry, stability to linear transformations etc). Following can be included in behavioral characteristics:

- Ability to express the behavior of the person making decisions (for example optimism, pessimism, seriousness);
- Semantic interpretability of parameters;
- Possibility of consideration of compensation effect or interaction among criteria.

Analysis conducted in [1], demonstrates that, all existing aggregation operators have some disadvantages. Majority of operators do not have all desired features. Besides, some of them are not capable of modeling interaction among criteria. Fuzzy integrals that are free from these disadvantages are the exceptions.

In this work, we are proposing the aggregation of results of three classifiers for multi-biometric systems based on fuzzy integrals, which allows increasing the accuracy of recognition.

## 2. Classifier for face image

There are different methods of classification of people by the image of their face: Principal Component analysis (PCA), Linear Discriminant Analysis (LDA) [2], comparison of elastic graphs [3], analysis of geometrical characteristics of a face, hidden Markov models.

Principal component analysis method was used for classification in this work. It is one of the main approaches for reducing the size of data, providing minimal loss of information. Distance from projection of test vector to middle vector of training set – Distance in Feature Space (DIFS) and distance from test vector to its projection on subspace of main components – Distance from Feature Space (DFFS) are determined. Based on these characteristics, decision on belonging of an object to one or another class is made.

Advantage of application of PCA is possibility of storage and search of images in large databases. Main disadvantage is requirement of high-quality image.

## 3. Fingerprint classifier

Research object in fingerprint recognition is the image derived from the scanner, which depicts a papillary pattern on finger surface. Recognition process based on fingerprints consists of following stages: filtration, binarization, attenuation, morphological processing (application of filters for deleting noise and improvement of image quality of the fingerprint), vectorization, vectorial post-processing, and comparison of two sets of special points [5].

Three algorithms of person's recognition based on fingerprints are known: correlation comparison, comparison based on special points, comparison based on pattern [4].

Upon correlation comparison, correlation among relevant special points of two images of fingerprints is calculated. Decision on identity of fingerprints is made based on coefficient of correlation.

In second method, special sample points and image of a fingerprint obtained through a sensor are compared. Decision on authenticity of the fingerprint is made based on the quantity of coinciding points. Due to simplicity of realization and high-speed of the work – given class algorithms are the most widely used.

Characteristics of structure of papillary pattern on the surface of fingers are considered in pattern comparison methods.

Method proposed in [5] was used as fingerprint classifier in this work. Given method has a high accuracy level and high-speed verification.

## 4. Iris classifier

One of the most perspective methods of user identification is iris recognition method. Concept of automatic recognition of iris was proposed by L.Flom and A.Safir in 1987 [6]. Several methods of iris recognition are known. Daugman [7] uses Gabor filters for modulation of phase information of iris texture. Filtration of the image of iris using a set of filters, results in 1024 complex-valued vectors, which describe the structure of iris in different scales. Afterwards, each phase is discretized on a complex surface. 2048-bit code of iris obtained as a result, is used for its description. Difference between pairs of iris codes is measured using Hamming distance.

Wildes [8] presents the texture of iris using Laplasian pyramids constructed by four different levels of resolution. Normalized correlation is used for comparison of entrance image with the reference.

Boles and Boashash [9] propose an iris recognition method based on wavelet-transformations, whereas resultant image is zeroed (zero-crossings of one-dimensional wavelet transforms). Comparison of irises is based on two dissimilarity functions.

## 5. Fuzzy integrals

In this section we will confine ourselves to minimal mathematical definitions. For more detailed information please refer to [10].

Let $x \in \{x_1,...,x_2\}$ mark the set of criteria and $P(x)$ – power set for $X$, i.e. set of all subsets of $X$ set.

**Definition 1.** $\mu : P(x) \to [0,1]$ function is the fuzzy measure on $X$ set, meeting following conditions:

1) $\mu(\varnothing) = 0, \quad \mu(X) = 1;$
2) $A \subseteq B \Rightarrow \mu(A) \le \mu(B)$.

$\mu\,(A)$ presents the significance of sets of $A$ criteria. Sugeno entered so called $\lambda$ – rules for structuring of fuzzy measures, meeting following additional properties: for all $A, B \subset X$, $A \cap B = \varnothing$ and some fixed $\lambda > -1$

$$\mu\,(A \cup B) = \mu(A) + \mu\,(B) + \lambda\mu\,(A)\mu\,(B).$$

Value of $\lambda$ can be found from the definition $\mu(X) = 1$, which is equivalent to the solution of following equation

$$\lambda + 1 = \prod_{i=1}^{n}(1 + \lambda\, g_i) \tag{1}$$

Let's suppose $A_i = \{x_i, x_{i+1}..., x_n\}$. When $\mu$ is $\lambda$ -fuzzy measure, then value of $g(A_i)$ can be calculated recursively following way:

$$\begin{aligned} &g\,(A_n) = g(\{x_n\}) = g_n \\ &g(A_i) = g_i + g(A_{i+1}) + \lambda g_i g(A_{i+1}), \qquad 1 \le i \le n. \end{aligned} \tag{2}$$

Depending on value of $\lambda$, two classes of fuzzy measures are reviewed: superadditive measures – belief measures and subadditive measures – credibility measures $(-1 < \lambda \le 0)$. fuzzy measure is called additive, if $\mu(A \cup B) = \mu(A) + \mu(B)$, upon $A \cap B = \varnothing$, superadditive (subadditive) $\mu\,(A \cup B) \ge \mu\,(A) + \mu\,(B)$ $(\mu(A \cup B) \le \mu(A) + \mu(B)$, upon $A \cap B = \varnothing$. Let's note that, if fuzzy measure is additive, then for definition of measure it is sufficient to calculate *n* of coefficients (weights) $\mu(\{x_1\}),...\mu(\{x_n\})$.

Now, let's introduce the definition of fuzzy integrals.

**Definition 2.** Let's suppose $\mu$ – is a fuzzy measure for $X$. Fuzzy integral of Choquet from function $f : X \to [0,1]$ on fuzzy measure $\mu$ is determined in following method:

$$C\mu(\,f(x_1),\, f(x_2),...,\, f(x_n)) = \sum_{i=1}^{n}(\,f(x_{(i)}) - f(x_{(i-1)}))\mu(A_{(i)}),$$

where $\cdot_{(i)}$ shows, that indexes are repositioned in following way: $0 \le f(x_{(1)}) \le ... \le f(x_{(n)}) \le 1$, $A_{(r)} = \{x_{(i),}..., x_{(n)}\}$ и $f(x_{(0)}) = 0.$

**Definition 3.** Let's suppose $\mu$ – is a fuzzy measure for $X$. Sugeno fuzzy integrals from $f : X \to [0,1]$ function on fuzzy measure $\mu$ are determined in following way:

$$\int_{\mu}(\,f(x_1),\, f(x_2),...,\, f(x_n)) = \max_{i=1}^{n}(\min(\,f(x_{(i)}), \mu(A_{(i)})),$$

Where denominations coincide with abovementioned.

Sugeno and Choquet integrals [11] are idempotent, continuous, monotone non-decreasing operators. This characteristics implicates that fuzzy integrals are always limited between min and max.

Choquet and Sugeno integrals are significantly different by their nature, as first integral is based on linear operators, and second one – on nonlinear operators (min and max).

An interesting feature of Choquet fuzzy integral is that, if $\mu$ is a probability measure, Choquet integral is equivalent to classic Lévesque integral and calculates the expectation of *f* with relevance to $\mu$ through traditional probability scheme.

Choquet integral is suitable for quantitative aggregation (where numbers have a real meaning), at the same time Sugeno integral is more suitable for serial aggregation (where only order has a meaning).

## 6. Fusion method of score values

In this work, we review *m* biometric characteristics: $x_1, x_2, \ldots, x_m$. For each biometric characteristic, $\mu(x_1), \mu(x_2), \ldots, \mu(x_m)$ fuzzy measures are determined. Based on formula (1), $\lambda$ is calculated. Furthermore, using formulas (2), fuzzy measures for all possible combinations of biometric characteristics: $\{x_1, x_2\}, \{x_1, x_3\}, \ldots, \{x_1, x_2, \ldots, x_m\}$.

Let's indicate obtained fuzzy measures through $\mu(A_1), \mu(A_2), \mu(A_3), \ldots$. Using the membership function, we fuzzify the score value, obtained during comparion of biometric characteristics. Use of obtained values of fuzzification and fuzzy measures allows calculating fuzzy integral.

## 7. Conclusion

In this work, we propose the use of Sugeno and Choquet fuzzy integrals for aggregation of results of classifiers in multi-biometric systems. Usage of additive measures (for example, probability measure) in structures of characteristic, results in repeated accountancy of the same characteristics and systematic error during evaluation. Non-additivity of Sugeno fuzzy measures allows prevention of this disadvantage. Proposed algorithm can be used in any subject field without limitation.

Importance of this method consists of not only fusion of classifier results, but also reviewing of each characteristic individually. Conducted analysis demonstrates that, application of fuzzy integrals is significantly better for aggregation of characteristics. Usage of fuzzy integrals significantly improves the identity check and makes multi-biometric system more stable to external changes.

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