Improved age prediction from biometric data using multimodal configurations

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Abstract— **The prediction of individual characteristics from biometric data which falls short of full identity prediction is nevertheless a valuable capability in many practical applications. This paper considers age prediction in two biometric modalities (iris and handwritten signature) and explores how different feature types and classification strategies can be used to overcome possible constraints in different data capture scenarios. Importantly, the paper also explores for the first time the use of multimodal combination of these two modalities in an age prediction task.**

Keywords—Age prediction; multimodal systems; intelligent agents

I. INTRODUCTION

Age prediction of individuals based on extractable physical and/or behavioural characteristics embedded in the individual's biometric data has become an important research topic in recent years. Estimating the age of an individual may be an important factor in obvious key applications such as forensic medicine or in the support of criminal investigations [1]. Increasingly, however, we see that the capability to predict age might also be extremely influential in situations relating to human-computer interaction, networking and security applications and, not least, in the determination of entitlement to age-limited goods and services. For example, nowadays there are significant pressures to develop an automated means of preventing young or vulnerable people from accessing Internet pages with prejudicial contents, or preventing those below a legally defined age limit from buying alcohol or cigarettes. It has been reported in [1], for example, that vending machines which are equipped with a capability for biometrics-based age estimation can help to solve this kind of practical issue. While there are many identification strategies or soft biometric prediction approaches which might be used, estimation of individual characteristics from biometric data is particularly useful, since this removes the need for seperate physical tokens, the formal inspection of documents, and so on.

In this paper, we will take some important steps towards a better understanding of how to define an optimal mechanism - the relationship between biometric feature types and age predictive capabilities - to predict age from biometric data which can be effectively matched to the operational requirements of both typical biometric and multibiometric platforms. Initially, we will focus on age prediction from two different individual biometric modalities, in this case the iris and the handwritten signature, the first representing a well-known physiological biometric modality, the second a behavioral one. Subsequently, in order to exploit the benefits of age prediction across the diverse range of potential application scenarios, the option of deploying multimodal biometric systems for the age prediction task will also be investigated. To the best of our knowledge, this is the first time multimodal configurations have been studied for this task.

II. STATE OF THE ART

A study of the literature shows that face biometrics have received the greatest attention in the research area of age estimation [1-7]. This is perhaps not surprising since it is particularly natural and easy to obtain facial images for applications such as criminal investigations or for networking purposes. Other relevant research which has also been reported in this context includes the estimation of age from, for example, voice characteristics [8, 9], palm [10], signature [11], iris [12, 13] and from fingerprint [10].

Considering facial biometrics, several different strategies have been proposed for age prediction, for instance, the reconstruction of facial ageing patterns to specify age [2, 3], usage of the spatial LBP histogram of regions of face images to predict the target age of individuals [4], an age manifold learning scheme for extracting face ageing features, and the design of a locally adjusted robust regressor for learning and prediction of human age [1]. In addition, it has also been shown that combining probabilistic methods with shape and texture information about the face achieved better age prediction results [5], which emphasises the importance of the choice of features of face images in the age prediction task. Hence, in the case of the face modality it can be useful to use regions of the face which are most sensitive to age variations. A possible method for finding these regions is proposed in [6] which uses the Adaboost algorithm.

There are not a large number of reported studies concerning age estimation from other biometric modalities, and this is still a comparatively new research area. However, in [8], a system for voice-based age estimation is proposed for telephone-related scenarios, and the most relevant parameters to classify voice are separated into three different age groups young (from 15 to 30 years old), adult (from 31 to 60 years old), and senior (from 61 to 90 years old) with an approximately 90% accuracy has been reported in [9].

A consideration of age estimation based on the handwritten signature modality, which is also especially useful for crime investigation and forgery detection, is presented for example in [11]. In this particular work, an analysis of how traditional classifiers behave, both individually and in combination, while performing age prediction is presented. Three age bands (age<25, 25-60 and age>60) from handwritten signature data were adopted and the error rates for each individual band was analysed. The proposed methodology achieves an approximately 5% mean error.

Similarly, a small amount of research has been reported in the literature which aims to predict age from iris biometrics. For instance, age prediction from iris biometrics is first studied in [12], and a classification technique which categorises a person into "young" (individuals whose age is between 22 and 25) or "old" (individuals whose age is greater than 35) age groups from the iris's texture-based characteristics with an accuracy of around 64.68% has been proposed. Subsequently, a more comprehensive study, using a different approach, is proposed in [13]. This adopts a combination of a small number of very simple geometric features, and a more versatile and intelligent classifier structure which can achieve accuracies up to 75% with three, rather than just two, age groups (<25, 25-60 and >60).

In summary, although it is thus possible to find some interesting and informative work dealing with age estimation based on various different biometric modalities, studies regarding the combination of modalities are more difficult to find. Also, as can be understood from the discussion above, it is very difficult to find studies that explore which feature types best reflects age-related information to maximise age estimation accuracy, except within the face modality. However, considering iris biometrics, it has been shown that ageing effects on the iris are primarily the result of the physiology of pupil dilation mechanisms, with pupil dilation responsiveness decreasing with age. Hence, since pupil dilation is clearly related to the geometric appearance of the pupil and the iris, this suggests that geometric features of the iris may provide more useful information for the age prediction task [13] rather than the more usually used texture features (as in [12]). Similarly, considering the signature, it has been shown that as subject age increases, features related to pen dynamics (e.g. velocity, acceleration, pen lifts) decrease in magnitude while, as a corollary, features related to execution time increase in magnitude [14-16], which suggests that the dynamic features of the signature may provide more useful information for the age prediction task than static features. However, the use of the iris patterning or signature characteristics for this purpose has not yet been fully investigated.

III. INVESTIGATING AGE ESTIMATION

Intuitively, it is advisable that an age estimation procedure should use as much information as is available (though, naturally, availablity can be minimised to enhance notions of privacy) in order to maximise the potential effectiveness of the prediction process. However, our study aims particularly to explore the relationship between biometric feature types and system predictive capabilities. In some cases, for example, the type of information available will be dependent on the actual physical sample capture process, while in other circumstances constraints on processing capability or the computational time window for feature extraction and related processing may limit the type of data which can be made available. Appropriate options should therefore be considered if we are to understand how to optimise performance while taking due account of the constraints imposed by factors which prevail in any particular practical situation. In fact, for both of our chosen modalities, such constraints may dictate the consideration of several different possible feature extraction options. Specifically:

Handwritten signature modality: it is well established that the features available in the processing of handwritten signature data may be of different types:

- Static features: These are features which describe measurements available only from the overall finished output of the signing process, such as overall shape descriptors, dimensional measurements and so on. They are typically the only features available when a conventional imaging approach (e.g. directly using a camera) is used for capture.

- Dynamic features: These are features which reflect time-based measurements associated with writing execution, and are thus only available where capture includes some form of pen trajectory monitoring. An archetypal dynamic capture process might, for example, be based on a digitising tablet, or some other on-line sample acquisition and can yield additional and richer information relating to pen velocities, stroke sequencing and other time-dependent aspects of signature *execution.*

- Pseudo-dynamic features: In some cases it may be possible to capture a static sample but then predict likely dynamics from this initial capture, but this is a much more limited and less well-established option which we will not consider here.

- Naturally, it is possible to integrate both static and dynamic features, since dynamic capture does not preclude the extraction of static measurements, and we will thus include a mix of such features as a further category to be considered here.

Iris modality: it is similarly possible to identify different feature categories, although not in quite such an infrastructure-determined way as for the signature. Nonetheless, we may identify the following categories:

- Texture features: These are features which describe the pattern of the iris available only from the overall finished output of the acquisition, segmentation, normalisation and feature extraction process respectively.
- Geometric features: These are features which describe the shape (physical appearance) of the iris, and are thus available only from the output of the acquisition and segmentation process respectively.
- And again, similarly, it is possible to identify a third option which is to integrate both geometric and texture features to provide a richer but more computationally intensive feature set.

By investigating attainable system performance with such different feature sets we will increase our understanding of how capture infrastructure and system configuration influence system performance profile in differing circumstances, and will thus allow us to explore which type of features provide the most appropriate and practically useful information (i.e. best reflecting ageing patterns) for age prediction with respect to iris and signature modalities. In addition, we will show how this can be effectively matched to the operational requirements of both typical biometric and multimodal biometric platforms through the application of intelligent classifier structures in this type of task. Some further details about our investigation is presented in the following subsections.

A. Description of the different features

We will thus work with different types of features for both the signature and the iris modalities in order to evaluate the real impact of using single and multisource data in the age prediction stage and explore how this might be balanced by adopting different classification structures, or perhaps more powerful and intelligent configurations.

For the signature modality a natural separation into static and dynamic feature sets yields the features for the static and dynamic cases shown in Table I. For the iris modality, each eye image is first segmented by using the segmentation algorithm described in [17]. In the event of segmentation failure (this occurred for only 1.87% of images), we segment the irises manually and make sure that all eye images are correctly segmented, in order to guarantee that our investigation reflects predictive capability rather than segmentation effects. Subsequently, in the case of geometric feature extraction, the obtained iris (i_x: x-coordinate of the centre of the iris, i_y: y-coordinate of the centre of the iris, i_r: iris radius) and pupil (p_x: x-coordinate of the centre of the pupil, p_y: y-coordinate of the centre of the pupil, p_r: pupil radius) parameters from the segmentation process are used and geometric features are extracted as shown in Table II. In the case of texture feature extraction, after the segmentation stage, normalisation (as described in [17]) is performed to unwrapped iris image of size 20*240 pixels, and then 1D Log-Gabor wavelets are used to encode features [18], which outputs a template of size 20*480 with both real and imaginary components. As in [19], we only use real components (which correspond to the array of complex numbers of size 20*240 of the template) to extract texture features, which are defined in Table II.

B. Age representation

Since age (human age progression) is a continuous variable, it is usual to divide a given target population into age bands for the age-related classification process. However, the age-bands adopted in age-prediction studies reported in the literature are found to vary considerably [5, 9, 11, 12] and, to an extent, are dependent on the biometric modality used. The choices made in this respect, often with no specified rationale, make inter-study comparisons and, indeed, any informed or objective choice of age bands, extremely difficult.

TABLE I. SIGNATURE STATIC AND DYNAMIC FEATURES

	Features	Description
Static	SF1	Signature Width
	SF2	Signature Height
	SF3	Height to Width Ratio
	SF4	Sum of horizontal coordinate values
	SF5	Sum of vertical coordinate values
	SF6	Horizontal centralness
	SF7	Vertical centralness
Dynamic	DF1	Total time of the signature
	DF2	Counts of the pen removal
	DF3	Pen velocity in the *x*
	DF4	Pen velocity in the *y*
	DF5	No of times midline is crosses
	DF6	Changing in the rotation with the z-axis
	DF7	Average angle toward the positive z-axis

TABLE II. IRIS GEOMETRIC AND TEXTURE FEATURES

	Features	Description
Geometric	GF1	Scalar distance between the x-coordinates of the centre of the iris and the pupil
	GF2	Scalar distance between the y-coordinates of the centre of the iris and the pupil
	GF3	Scalar distance between the centre of the iris and the pupil
	GF4	Total area of the iris
	GF5	Iris radius divided by pupil radius
Texture	TF1	Mean of the real components in row x
	TF2	Standard deviation of the real components in row x
	TF3	Variance of the real components in row x
	TF4	Mean of the real components in col y
	TF5	Standard deviation of the real components in col y
	TF6	Variance of the real components in col y

Hence, in this study, we have partitioned the population into these three age groups: <25, 25-60 and >60, providing the opportunity to explore age-related effects across broad but meaningful user categories (younger, middle-aged, and older) while maintaining a good representation of users in each sub-group. This also directly addresses some particular practical scenarios. For example; the legal alcohol drinking age embodied in the laws which regulate the sale and consumption of alcohol in India (in many cities) is the age of 25 [21]. In any case, a division into our choosen groupings allows easy comparison with several other important relevant reported studies which use the same age-group boundaries.

C. *Intelligent structures for enhanced processing*

Finding a balance between competing design criteria in biometric-based systems is always a very challenging task. However, it is often possible to compensate for a perceived weakness in one step by appropriate modifications at another step. This is a principle which we embrace here, in order to explore whether in some cases simplicity in feature choice may still offer performance viability when “intelligent” techniques, such as targeted machine learning or multiagent systems are deployed.

In this context we will investigate the adoption of some traditional multiclassifier techniques and some multiagent techniques for our experimentation by using a decision-level fusion approach. These can be summarised as follows, while more detailed descriptions can be found in [22]:

- Sum-based fusion (Multiclassifier system)
- Majority Voting (Multiclassifier system)
- Game Theory-based Negotiation Method (Multiagent system)
- Sensitivity-based Negotiation Method (Multiagent system)

The pool of base classifiers selected for the experimental study is as follows: Multi-Layer Perceptron (MLP) [23] with learning rate of 0.001 neurons in the intermidiate layer, momentum of 0.9 and 10000runs, Support Vector Machines (SVM) [24] with compexity parameter of 8 and learning rate of 0.001, Optimised IREP (Incremental Reduced Error Pruning) (JRip) [25] with minimal meight of 3 and radom initial seed of 2 and K-Nearest Neighbours (KNN) [26] using an Euclidean distance and K=3. We have chosen to use these classifiers in order to guarantee a high diversity among the individual components, which is essential in the context of multiclassifier configurations.

D. *Biometric database*

The database used in our study is the Data Set 2 (DS2) of the BioSecure Multimodal Database (BMDB) which was collected as part of an extensive multimodal database by 11 European institutions participating in the BioSecure Network of Excellence [27], and is a commercially available database.

For the handwritten signature, the samples were collected using an A4-sized graphics tablet with a density of 500 lines per inch. Each user donated 30 genuine samples of a handwritten signature in two sessions. In the iris, eye images were acquired in a standard "office" environment managed by a supervisor and using the LG Iris Access EOU3000. During the acquisition, spectacles were not allowed to be worn by subjects, although contact lenses were allowed. Eight eye images (four left and four right) were acquired in two different sessions with a resolution of 640*480 pixels.

The 210 subjects providing both the handwritten signature and the iris samples contained in this database are within the age range of 18-73. The iris samples of 10 subjects were found to be incorrectly labelled for the case of the iris database (some of the left eye samples labelled as right or right eye samples labelled as left). Hence, those subjects are removed from both the handwritten signature and iris datasets and this decreased the available number of subjects to 200.

In this study, we have considered both the age and the identity labels of subjects while dividing the overall population into testing and the training sets. Hence, we make sure that the same subjects’ samples are included only in the testing or only in the training set. The available number of subjects in the testing and the training sets for both the signature and the iris modalities is shown in Table III.

E. Unimodal and multimodal biometric age prection systems

For age prediction from an unimodal biometric system (i.e. only iris or only the handwritten signature); prediction accuracy (on three age groups – see section III B) is evaluated with respect to each feature type (see section III A) by using both multiclassifier and multiagent systems (see section III C and III E).

For age prediction using a multimodal system; prediction accuracy (on three age groups – see section III B) is evaluated with respect to the feature type (see section III A) by using both multiclassifier and multiagent systems (see section III C and III E) on each modality and then the obtained scores are used to make the final decision (decision-level fusion is used to combine iris and signature).

TABLE III. NUMBER OF SUBJECTS PER AGE BAND

Sets	<25	25-60	>60
All	70	115	15
Train	50	82	11
Test	20	33	4

IV. EXPERIMENTS AND RESULTS

A particular aim in this study is to provide a better understanding of how to define an optimal mechanism to predict age from handwriten signature and iris biometric data which can be effectively matched to the operational requirements of a typical unimodal and multimodal age prediction system.

An initial experiment is performed to establish the achievable accuracy of the proposed age prediction approach with respect to the defined different types of features and different individual classifiers -by using the methodologies set out in Section III- for both the iris and signature modalities. The results are shown in Table IV.

In the case of the iris, better performance is achieved by using texture features rather than geometric features. This is somewhat surprising since the geometric appearance of the iris changes with age while the texture does not [28]. However, since the performance difference is relatively modest, it is fair to say that this may be an effect of the differing classification techniques. This will be explored and discussed after reporting the second experiment.

In the case of the signature, better performance is achieved by using dynamic features than when static features are deployed. This is not surprising since it has been shown that as subject age increases, features related to pen dynamics (e.g. velocity, acceleration, pen lifts) decrease in magnitude while, as a corollary, features related to execution time increase in magnitude [14-16]. As we suggested earlier this shows that the dynamic features of the signature typically provide more useful information for the age prediction task than the static features.

When we compare the results for the two modalities, age prediction accuracy from the handwritten signature is better than for iris biometrics for all types of features and individual classifiers. However, the most significant performance difference occurs when dynamic features are added in the case of signature. Hence, this shows that the behavioural nature (dynamic features) of the signature carries more distinct information about the age than the iris - physiological-characteristics.

Therefore, considering all the individual classifiers, the age prediction accuracy of both iris and signature modality is seen to between 55% and 75%.

TABLE IV. TACCURACY OF INDIVIDUAL CLASSIFIERS PERFORMING AGE PREDICTION WITH DIFFERENT FEATURE DISTRIBUTIONS FOR BOTH IRIS AND SIGNATURE

Modality	Feature type	Classifiers			
		KNN	***Jrip***	***MLP***	***SVM***
Iris	Geometric	52.41	55.94	57.69	59.62
	Texture	55.68	62.50	61.80	62.06
	All	59.84	63.87	62.46	65.99
Signature	Static	60.22	63.81	64.38	65.90
	Dynamic	62.37	68.11	71.92	71.24
	All	63.66	69.22	73.64	72.10

Subsequently, in order further to investigate how iris and signature could be most effectively exploited for age prediction, a second experiment is performed to define an optimal mechanism to predict age from handwritten signature and iris biometric data which can be appropriately matched to the operational requirements of a typical multimodal configuration.

All possible iris and signature feature combinations are considered and the age prediction accuracy evaluated with decision level combination by using the methodology defined in Section III. The results obtained are shown in Table V.

The first general observation regarding these results is that all the fusion techniques produce better results than the individual classifiers. Also, all the agent-based negotiation techniques perform better than all the traditional fusion techniques, with sometimes more than 10% difference in accuracy. Secondly, when all features are used for both modalities, the best accuracy is achieved and, in some cases, there is a considerable difference compared with the other scenarios, as when the fusion technique is an agent-based solution. And finally, the performance difference that had arisen because of using different feature types for both iris and signature modalities, can be seen to be significantly reduced when agent-based classifiers are used.

Hence, this shows that using appropriate types of features may best reflect ageing related information. However, in practical situations, where the choice of features may be restricted, we can see that more powerful or sophisticated classifiers (here, for example, the agent-based configurations) can be used to compensate for a less discriminatory feature set.

As a summary, our proposed multimodal (in our study, iris and signature) age prediction system is able to achieve accuracies up to 90% while the unimodal age prediction systems are able to achieve accuracies up to 75%. Also, all these results point to some interesting observations such as: the signature appears to be more effective for age prediction than the iris modality, and intelligent processing techniques can be adopted as a counter-balance to the constraint of a lack of information that may be expected in some application environments.

TABLE V. ACCURACY OF DIFFERENT COMBINATIONS OF FEATURES IN MULTIMODAL SYSTEM

Modality and feature type	Classifiers			
	Vote	*Sum*	*Sensitivity*	*Game*
Iris Geometric* + *Sig. Static	69.99	66.92	77.34	75.29
Iris Texture* + *Sig. Static	67.97	66.38	79.66	76.84
Iris Geometric* + *Sig. Dynamic	72.41	72.93	79.63	76.98
Iris Texture* + *Sig. Dynamic	74.81	75.83	80.33	79.84
Iris All* + *Sig. All	78.66	80.26	91.07	89.33

V. CONCLUSION

In this paper we have investigated experimentally some approaches to age prediction from iris images and signature samples which use different types of features for both individual modalities and the combination of modalities with an intelligent classifier structure which we have found in other studies to be especially well suited to more conventional identity prediction from biometric data [29].

The performance we have been able to achieve - assigning each tested subject to one of three age groups (corresponding to "younger", "middle-aged" and "older" categories) in relation to prediction accuracy, even with a limited feature set, is seen to be very encouraging. We should note also that further performance improvements are likely to be achievable by defining a more extensive basic feature pool (especially in the case of the signature), or exploring optimisation of the classifier configurations.

This comparative study based on different feature sets (i.e. geometric, texture and both for the iris, and static, dynamic and both for the signature) and different classification approaches, will provide the system designer with useful information by means of which to develop targeted strategies to consider the choice of feature and classification approaches in relation to particular application requirements.

We regard these experimental results as most encouraging in a task domain which has not yet been extensively investigated to date. Although further work is required to improve and enhance the levels of achievable performance, our reported results show real promise in relation to the suitability of our basic techniques for application to a number of practical scenarios of importance and considerable current interest.

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