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.

1 Introduction

Age prediction of individuals based on extractable physical and/or behavioural characteristics embedded in the individual's biometric data has become an important factor in obvious key applications such as forensic medicine, in the support of criminal investigations,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 [G08]. 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 separate 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.

2 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 [XZS07], [G08], [CY09], [NG14]. Other relevant research which has also been reported in this context includes the estimation of age from, for example, voice characteristics [M07], [Mf10], palm [LT11], signature [FA09], iris [SBF13], [EFA13] and from fingerprint [LT11].

A consideration of age estimation based on the handwritten signature modality is presented for example in [FA09]. 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 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 [SBF13], and a classification technique which categorises a person into "young" or "old" age groups from the iris's texture-based characteristics with an accuracy of around 64.68% has been proposed. Subsequently, a more comprehensive studyis proposed in [EFA13]. 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 .

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 and feature types which best reflects age-related information to maximise age estimation accuracy are more difficult to find.

3 Investigating age estimation

This 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:

- Static features: describe measurements available only from the overall (completed) output of the signing process. They are typically the only features available when a conventional imaging approach is used for capture.
- Dynamic features: reflect time-based measurements associated with writing *execution*, and are thus only available where capture includes some form of pen trajectory/timing monitoring.
- Naturally, it is possible to integrate both static and dynamic features, since dynamic capture does not preclude the extraction of static measurements.

Iris modality:

- Texture features: 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: describe the shape 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 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 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.

3.1 Description of the different features

For the signature modality a natural separation into static and dynamic feature sets yields the features for the static and dynamic cases exemplified in Table 1. For the iris modality, geometric and texture features shown in Table 1are extracted as in [EFA13].

3.2 Age representation

Since age 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 [Mf10], [SBF13], [FA09]. 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. In this study, we have partitioned the population into three age groups as suggested in [EF12]: <25, 25-60 and >60, providing the opportunity to explore age-related effects across broad but meaningful user categories while maintaining a good representation of users in each sub-group.

		Features	Description
Signature	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
Iris	Geometric	GF1	Scalar distance between the x-coordinates of the centre of the iris
		GF2	Scalar distance between the y-coordinates of the centre of the iris
		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*

Table 1: Signature and iris features

3.3 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 [AF11b]: 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) [H08], Support Vector Machines (SVM) [CS00], Optimised IREP (Incremental Reduced Error Pruning) (JRip) [FW94] and K-Nearest Neighbours (KNN) [A98].

3.4 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 [Og10], and is a commercially available database. The 210 subjects providing both the handwritten signature and the iris samples contained in this database are within the age range of 18-73. 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.

3.5 Unimodal and multimodal biometric age prediction systems

For age prediction from a unimodal biometric system, prediction accuracy is evaluated with respect to each feature type by using both multiclassifier and multiagent systems. For age prediction using a multimodal system, prediction accuracy is evaluated with respect to the feature type by using both multiclassifier and multiagent systems 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).

4 Experiments and results

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 for both the iris and signature modalities. The results are shown in Table 2.

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 typically does not [Gj13]. 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 [G06]. 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 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 lie between 55% and 75%.

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

Table 2: Accuracy of individual classifiers performing age prediction with different feature distributions for both Iris and Signature

Subsequently, in order further to investigate how iris and signature (illustrative of a general multimodal option) 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. The results obtained are shown in Table 3.

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 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 general observations. For example, 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. These are useful guidelines to bear in mind in moving to specific application scenarios.

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

Table 3: Accuracy of different combinations of features in multimodal system

5 Conclusions

The performance we have been able to achieve in relation to age 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, or exploring optimisation of the classifier configurations.
This comparative study, based on different feature sets and different classification approaches, are able to provide a 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 extremely positive, especially in a task domain which has not yet been extensively investigated to date.

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