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Publisher's version / Version de l'éditeur:

<https://doi.org/10.1109/HAVE.2013.6679618>

2013 IEEE International Symposium on Haptic Audio Visual Environments and Games (HAVE), pp. 98-102, 2013-11-01

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Identity Verification based on Haptic Handwritten Signature: Novel Fitness Functions for GP framework

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Abstract—Fitness functions are the evaluation measures driving evolutionary processes towards solutions. In this paper, three fitness functions are proposed for solving the unbalanced dataset problem in Haptic-based handwritten signatures using genetic programming (GP). The use of these specifically designed fitness functions produced simpler analytical expressions than those obtained with currently available fitness measures, while keeping comparable classification accuracy. The functions introduced in this paper capture explicitly the nature of unbalanced data, exhibit better dimensionality reduction and have better False Rejection Rate.

I. INTRODUCTION

The term Haptic comes from the Greek verb *haptikos* that means *to touch* and when applied to technologies implies tactile (reactive) feedback specifically based on the sense of touch. Essentially it involves the application of motions, vibrations and forces to a user that is interacting with a simulated environment with the aim of exploring, controlling or acting upon objects existing within the environment. In the same way, it allows a closer look at the mechanisms associated to the functioning of the human sensing system by keeping track of the forces exerted by the user when interacting with simulated objects. Ultimately haptic-based technologies will enable the human control and operation of remote objects like devices, patients or complex machinery in hazardous environments. Also it will lead to a better understanding of the human brain and its underlying functions.

The nature of haptic data is given basically by force and torque information, as well as positions, velocities and orientations in streams produced at the level of the sensing devices during the time in which the interaction with the virtual or real objects takes place. Overall it also provides trajectory and kinesthetic information. Since that interaction may cover extended periods of time, the body of information typically consists of high volumes of multidimensional time dependent

data, where it is common to have thousands of descriptive features.

The spectrum of application of haptic technologies has been expanded continuously since its inception to cover fields like the entertaining and gaming industries, military operations and even medicine [1], [2], [3], [4]. Security technologies are gradually looking into incorporating haptic-based solutions to their sets of identification and verification tools. In particular, biometric systems try to identify humans by their distinctive physical and/or behavioral characteristic. They can be purely physical, or physiological, or psychological and examples are classical fingerprint, hand geometry, face features, DNA, iris/retina properties, etc. Accordingly, the incorporation of haptic-based biometric tools becomes natural in order enhance the effectiveness of the systems by means of which critical services or allowances are granted to users. In recent years haptic-based techniques to improve user identification/verification have been introduced, for example, through the use of haptic handwritten signatures [2], [4].

From a biometric perspective two related but differentiated user authentication problems are considered: verification and identification. In the former case, the task is to check whether the identity of a person, as described by what could be called his biometric template originally stored within the system acceptably matches the current state of the same set of biometric descriptors obtained from the person. Regardless of the approaches used for comparing the stored with the actual biometric characterization, or the measure used to produce the evaluation (crisp, fuzzy, probabilistic, etc.) the system must come to a binary decision as to whether to declare the given identity as verified or not.

In identity identification, the problem is to determine if the current biometric characterization of a person matches one (or perhaps more) of the individuals from which biometric templates are available to the system as a resource database.

Therefore it is a one-to-many problem in contradistinction to verification, which is one-to-one. Haptic-based verification and identification is a rapidly growing research area. Initial work was done on proof of concept applications like virtual maze environment [5]. Using Hidden Markov Models, spectral analysis and time warping techniques for haptic user verification purposes, accuracies of the order of 78.8% were obtained, with a 25% False Acceptance Rate (FAR). The feasibility of haptic-based user authentication was explored in [2] where in addition to the virtual maze, a haptic handwritten signature application in the form of a virtual bank check was developed. Verification rates of 92% with a 25% FAR were achieved.

For the haptic-based handwritten application, GP was used for feature selection and classification with unbalanced datasets [6]. In that case the possibilities of GP as a dual tool for simultaneous feature generation/reduction as well as for classification were shown. On average, for all datasets (imbalanced or random under-sampled), several perfect classification models were found as well as great feature reduction rates via feature selection. That is, compact analytic expressions with high classificatory power. In this paper, we present three custom fitness functions that are used by GP to solve the unbalanced dataset problem. The utilization of fitness functions, rather than applying sampling techniques, allows the use of the entire dataset and also reduces the overhead caused by the introduction of additional procedures.

The paper is organized as follows: Section II describes genetic programming and present the proposed fitness functions. In Section III contains the experimental settings and discuss the haptic signature data and application. Section IV presents the results and the conclusive remarks are covered in Section V.

II. GENETIC PROGRAMMING: GENE EXPRESSION PROGRAMMING

Genetic Programming (GP) is one of the evolutionary computation techniques inspired on the evolution of biological life in nature. The process evolves functions and programs (analytical models) with the goal of finding optimal solutions. The individuals evolved are analytic functions representing computer programs with univariate or multivariate target variables. The analytic expressions are obtained by applying operators to a given set of base functions, including constants. GP was introduced in [7] and further elaborated in [8], [9] and [10]. GP starts with an initial population which consist of a set of individuals. Then the population evolves from one generation to the next by applying several operations such as recombination of entities (crossover), occasional mutation, duplication and gene deletion. The operations include arithmetic computation, conditionals, iterations, recursions, code reuse and other kinds of information processing organized into a hierarchy.

There are many flavors of genetic programming and one of them is Gene Expression Programming (GEP) [11], [12]. GEP individuals are represented as nonlinear entities of different sizes and shapes (expression trees) encoded as strings of

fixed length. A special translation technique named KARVA translates expression trees to non-linear strings and vice versa. GEP combines the simplicity of Genetic Algorithms (GA) and avoid the disadvantage of producing a non valid solutions in GP.

A. The Unbalanced Dataset Problem

An important element to consider is the unbalanced nature of the haptic dataset used in this work. In the case of binary classification, this problem occur when the number of instances belonging to a class (the majority class) is significantly larger than the number of instances belonging to the other class (the minority class). Such situation effects the classifier's performance especially when overall accuracy is the method of evaluation. More specifically, high overall accuracies can be obtained by predicting most (or all) of the majority class and little (or even none) of the minority class. Since this is not a desirable behavior, solving the unbalanced dataset problem means not compromising the accuracy of the minority class prediction. There are many solutions proposed for this problem such as re-sampling, cost assignment [13], [14], [15], and the utilization of specially designed fitness functions. In the context of genetic programming, custom fitness functions can be utilized to guide the evolutionary process in ways to consider the situation of unbalanced dataset [16], [17], [18], [19]. In this paper, we followed the aforementioned approach within the GP framework.

B. Genetic Programming's Fitness Functions for Unbalanced Datasets

When considering the unbalanced dataset problem where an overall classification accuracy is used for evaluation, one method that can be applied is the use of specially designed fitness functions. Such functions may take into account both the majority class and the minority class accuracies and guide the evolutionary process towards solutions that avoids the unbalanced dataset problem via better individual selection. In this paper, three new fitness functions are proposed, and their performance with respect to others proposed elsewhere [BH1, BH2, PA1, PA2] [20], [16] is compared. The newly introduced fitness functions are:

$$SL = \frac{\left(\frac{N_{min}}{N_{max}} \times hits_{max}\right) + \left(\left(1 - \frac{N_{min}}{N_{max}}\right) \times hits_{min}\right)}{2 \times N_{min} - \frac{N_{min}^2}{N_{max}}} \quad (1)$$

This function tries to account for the minority class accuracy while considering the overall accuracy, where N_{min} and N_{max} are the number of instances for the minority class and the overall number of instances, respectively. $hits_{max}$ denotes the overall correct classification and $hits_{min}$ is the correct minority class prediction.

The second fitness function proposed is a non-linear one that considers the overall accuracy, in addition to the minority class and the majority class.

$$SNL = \frac{\frac{hits_{min}}{N_{min}} + \left(\frac{hits_{maj}}{N_{maj}}\right)^2 + \frac{hits_{max}}{N_{max}}}{3} \quad (2)$$

where $hits_{maj}$ is the number of correct classification elements of majority class, and N_{maj} is the total number of majority class instances.

The third proposed fitness function is also non-linear and considers both the minority class and the majority class, giving higher impact to the latter

$$exp = \frac{\frac{1}{1+e^{\left(\frac{Hits_{min}}{N_{min}}\right)^2}} + \frac{1}{1+e^{\frac{Hits_{maj}}{N_{maj}}}} - 1}{\frac{2}{1+e} - 1} \quad (3)$$

For baseline comparison, four additional fitness functions were considered. They were introduced in [20], [16] and consider both the majority class and the minority classes:

$$BH1 = \sqrt{\frac{hits_{min}}{N_{min}} \times \frac{hits_{maj}}{N_{maj}}} \quad (4)$$

Equation 4 represents a geometric mean combination of the classifier's performance for both classes.

The second fitness function introduced in [16] conceptually follows a similar idea as that of Equation 4, with the additional consideration of a third objective. It represents the overall classification accuracy, in addition to the accuracies of the individual classes:

$$BH2 = \frac{hits_{min}}{N_{min}} + \frac{hits_{maj}}{N_{maj}} + \frac{hits_{max}}{N_{max}} \quad (5)$$

The other two baseline fitness functions were introduced in [20] as

$$PA1 = \frac{\frac{hits_{maj}}{N_{maj}} + \frac{hits_{min}}{N_{min}}}{2} \times 100\% \quad (6)$$

$$PA2 = \frac{\left(\frac{hits_{maj}}{N_{maj}}\right)^2 + \left(\frac{hits_{min}}{N_{min}}\right)^2}{2} \times 100\% \quad (7)$$

They exhibit high classification performance when applied to several synthetic and real datasets from the point of view of the accuracy of the minority class.

III. EXPERIMENTAL SETTINGS

A. GEP Settings

The GEP experiments were performed using the implementation from [21], which extends the ECJ environment [22]. The parameter values used in the experiments are shown in Table I which have proved to be reasonable general choices for a broad variety of problems[23].

The mathematical expressions are composed of one chromosome per individual and each chromosome contains 3 gene expressions, all linked by the addition operator. The gene expressions can be formed using constants, the independent variables associated with each problem, and any of the functions from the function set. Weights can be associated to

TABLE I
EXPERIMENTAL SETTINGS OF THE GEP ALGORITHM.

GEP Parameter	Experimental Values
No. generations	100000
Population size	1000
No. chromosomes / individual	1
No. genes / chromosome	3
Gene head size	8
Linking function	addition
No. constants / gene	2
Bounded range of Constants	[0,10]
Inversion rate	0.1
Mutation rate	0.044
is-transposition rate	0.1
ris-transposition rate	0.1
One-point recombination rate	0.3
Two-point recombination rate	0.3
Gene recombination rate	0.1
Gene transposition rate	0.1
rnc-mutation rate	0.01
dc-mutation rate	0.044
dc-inversion rate	0.1
Function set (e.g., {function ₁ (weight) }, function ₂ (weight), ... })	{add(1), sub(1), mult(1),div(1)}

Fig. 1. Haptic-enabled virtual check application.

the functions in $\mathcal{F}$ in order to bias the evolutionary process towards the use of certain functions more than others. This is another mechanism that allows the introduction of external knowledge. In the present case all functions had the same weights.

For each experiment a set of 100 runs were performed with random seeds. In order to provide a rich genetic diversity at the onset of the evolutionary process, a larger than usual value of population size was chosen.

B. Haptic-Signature Data and the Virtual Check Application

The haptic handwritten signature experiment was performed using the Reachin Display [24]. In addition, the force feedback is felt through the use of the SensAble PHANTOM Desktop force-feedback device by an encoder stylus with 6-degree-of-freedom single contact point interaction and positional sensing.

The virtual check depicted in Fig. 1 represents the visual stimulus on top of which handwritten signatures are recorded. The encoder styles provides the haptic stimuli by providing force and frictional feedback. The check is built as an elastic

membrane surface that provides a realistic look and feel in the virtual environment.

On this experiment, 13 participants contributed ten haptic-enabled handwritten signatures each. A total of 130 handwritten signatures were collected, each one described in terms of 10,000 attributes associated to haptic features represented by position, forces, torque, and orientation with respect to the three coordinate axis. As the identity verification problem is a binary classification one, the dataset is rearranged where the instances of user of concern considered the positive class and the remaining instances are the negative class. Furthermore, the datasets are divided into 60% training and 40% testing.

IV. RESULTS

For each class, 100 different analytical functions are generated resulting from the evolution using the training dataset and the GEP model with the best discrimination performance is chosen.

The analysis of classification performance is based on the verification success rate (VR), the False Acceptance Rate (FAR), and the False Rejection Rate (FRR). They are shown in Table II, where the GEP evolutionary process is evolved with various fitness functions (NH, BH1, BH2, PA1, PA2, SL, SNL, EXP). NH represents the Number of Hits or the number of instances classified correctly. The classification results presented are based on the average performance of all generated models per class. Moreover, the average classification performance for the first quartile of the top GP models is shown in Table III. In Tables II, III, "No. of variables" represents the number of occurrences of predictor attributes within a given expression. The number of occurrences of functions from the function set $\mathcal{F}$ are represented by "No. of Operations". Both combined give an indication of analytic model complexity and dimensionality from the point of view of the amount of predictor variables involved.

From Table II and Table III, the average number of variables present in GP models (in all of them, as well as in the best ones corresponding to the first quartile of the error distribution) is considerably smaller than the total number of features (10,000). Moreover, the use of the proposed fitness functions capturing explicitly the behavior in the presence of unbalanced data (EXP, SNL, SL) resulted in additional dimensionality reduction (Table II). GP-generated models using fitness functions (BH1, BH2, PA1, PA2, EXP, SNL, SL) exhibited a decrease in FRR and slight increase in FAR. In certain types of applications, end users prefer systems with low FRR (0% as the ideal). From Table II and III, it is clear that the introduced fitness functions (EXP, SNL, and SL) outperformed the reference baseline function (NH) and some of the previously defined ones (BH2, PA1). An extreme dimensionality reduction is observed in all GP-generated models. On the other hand, the use of fitness functions (BH1, BH2, PA1, PA2, EXP, SNL, SL) resulted in a less complex analytical functions where the number of mathematical operations within the model is significantly less than the one observed with the use of NH as a fitness function. The use of the proposed fitness

functions (SL, SNL, EXP) resulted in a significant decrease in FRR (with the lowest at 15.15%) as illustrated in Table III. A similar behavior is found only with the use of fitness functions (PA2, BH1).

TABLE II
CLASSIFICATION RESULTS BASED ON THE AVERAGE PERFORMANCE OF ALL GP-GENERATED ANALYTICAL FUNCTIONS (100 ANALYTICAL FUNCTIONS PER CLASS) WITH VARIOUS FITNESS FUNCTIONS.

Fit.Func	60%				
	VR (%)	FAR (%)	FRR (%)	No. of Variables	No. of Operations
NH	91.49	5.65	42.85	7.67	22.63
BH1	89.27	8.44	38.15	6.22	8.46
BH2	89.77	7.92	37.98	6.18	8.26
PA1	89.67	8.00	38.29	6.30	8.57
PA2	89.83	7.94	36.87	6.04	8.23
EXP	89.80	8.01	36.50	6.19	8.65
SNL	89.85	7.84	37.85	5.93	7.75
SL	89.75	7.98	37.56	6.35	8.69

TABLE III
CLASSIFICATION RESULTS BASED ON THE AVERAGE PERFORMANCE OF THE FIRST QUARTILE OF THE BEST GP-GENERATED ANALYTICAL FUNCTIONS (PER CLASS) WITH VARIOUS FITNESS FUNCTIONS FOR 13 USERS.

Fit.Func	60%				
	VR (%)	FAR (%)	FRR (%)	No. of Variables	No. of Operations
NH	95.90	1.93	30.13	7.39	22.88
BH1	92.89	6.34	16.31	5.97	7.74
BH2	91.84	6.56	27.31	5.84	7.32
PA1	91.34	7.19	26.31	6.10	8.14
PA2	93.25	5.90	16.92	5.73	7.87
EXP	93.14	6.17	15.15	6.02	8.05
SNL	93.18	5.98	16.92	5.94	7.86
SL	92.91	6.32	16.35	6.17	8.32

The use of GP-generated models allows a closer analysis of the contribution of haptic features. As an example, the frequency distributions of different haptic data for NH and EXP fitness functions are illustrated as box plots in Fig. IV.

From Fig. IV, it can be noticed that position information (P_x , P_y , and P_z) appeared in GP models with a probability of approximately equal to 50% (a similar probability to that of the rest of the haptic features combined). The overall contribution of the purely haptic features is about 50% of the total probability which is about the same as the contribution coming from classical position features. This clearly indicates the importance of considering haptic information for classification purposes.

V. CONCLUSION

In this paper, identity verification based on haptic based handwritten signature is examined through the utilization of Genetic Programming (GP). In addition, as the identity verification problem is affected by the unbalanced dataset problem, three specially designed fitness functions were proposed. They produced simpler equations than those obtained with baseline functions and yet exhibit high classification performance. The

Fig. 2. Box plots illustrating the frequency of haptic features found in GP-generated models. when Left: unbalanced dataset are considered with NH fitness function. Right: the proposed equation. 3 are considered as a fitness function. Each box includes lines referring to the median and the mean, in addition to the first and third quartiles. Whiskers are provided to show the extent of the frequency of different haptic features found in GP-models. 'o' symbol illustrates Outliers.

functions introduced here capture explicitly the nature of unbalanced data, exhibit better dimensionality reduction and have better False Rejection Rate. It was found that the use of haptic features brings valuable additional information to the identity verification process. Future work would cover a more comprehensive comparison with other fitness functions and classical classifiers.

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