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Computationally Inexpensive Sequential Forward Floating Selection for Acquiring Significant Features for Authorship Invarianceness in Writer Identification

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ABSTRACT

Handwriting is individualistic. The uniqueness of shape and style of handwriting can be used to identify the significant features in authenticating the author of writing. Acquiring these significant features leads to an important research in Writer Identification domain where to find the unique features of individual which also known as Individuality of Handwriting. This paper proposes an improved Sequential Forward Floating Selection method besides the exploration of significant features for invarianceness of authorship from global shape features by using various wrapper feature selection methods. The promising results show that the proposed method is worth to receive further exploration in identifying the handwritten authorship.

KEYWORDS

computationally inexpensive, feature selection, authorship invarianceness, significant features, writer identification.

1 INTRODUCTION

Feature selection has become the focus of research area for a long time. The purpose of feature selection is to obtain the most minimal sized subset of features [1]. Practical experience has shown that if there is too much irrelevant and redundant information present, the performance of a classifier might be degraded. Removing these irrelevant and redundant features can improve the classification accuracy.

The three popular methods of feature selection are filter method, wrapper method, and embedded method has been presented in [2]. Filter method assesses the relevance of features [3], wrapper method uses an induction algorithm [4], while embedded method do the selection process inside the induction algorithm [5]. Studies have shown that there are no methods more superior compared to others [6]. The selection of the methods to use sometimes depends on the size of the data itself. Using filter methods means to have a good computational complexity, but the higher complexity of the wrapper methods will also produce higher accuracy in the final result, whereas embedded methods are intrinsic to some learning algorithm and so only those algorithm designed with this characteristic can be used.

Writer Identification (WI) can be included as a particular kind of dynamic biometric in pattern recognition for forensic application. WI distinguishes

writers based on the shape or individual style of writing while ignoring the meaning of the word or character written. The shape and style of writing are different from one person to another. Even for one person, they are different in times. However, everyone has their own style of writing and it is individualistic. It must be unique feature that can be generalized as significant individual features through the handwriting shape.

Many previous works on WI problem has been tried to be solved based on the image processing and pattern recognition technique [7], [8], [9], [10], [11] and involved feature extraction task. Many approaches have been proposed to extract the features for WI. Mostly, features are extracted from the handwriting focus on rigid characteristics of the shape such as [7], [9], [11], [12], [13], [14], [15], [16], [17] except by [18] and [19], focus on global features.

The main issue in WI is how to acquire the features that reflect the author of handwriting. Thus, it is an open question whether the extracted features are optimal or near-optimal to identify the author. Extracted features may include many garbage features. Such features are not only useless in classification, but sometimes degrade the performance of a classifier designed on a basis of a finite number of training samples [20]. The features may not be independent of each other or even redundant. Moreover, there may be features that do not provide any useful information for the task of writer identification [21]. Therefore, feature extraction and selection of the significant features are very important in order to identify the writer, moreover to improve the classification accuracy.

Thus, this paper focuses on identifying the significant features of word shape by using the proposed feature selection method prior the identification task. The remainder of the paper is structured as follows. In next section, an overview of individuality of handwriting is given. Global feature representation by United Moment Invariant is described in Section 3. Section 4 provides an overview of proposed feature selection method, followed by the proposed approach to identify the significant features in Section 5. Finally, conclusion and future work is drawn in Section 6.

2 AUTHORSHIP INVARIANCENESS

Handwriting is individual to personal. Handwriting has long been considered individualistic and writer individuality rests on the hypothesis that each individual has consistent handwriting [10], [18], [23], [24], [25]. The relation of character, shape and the style of writing are different from one to another.

Handwriting analysis consists of two categories, which are handwriting recognition and handwriting identification. Handwriting recognition deals with the contents conveyed by the handwritten word, while handwriting identification tries to differentiate handwritings to determine the author. There are two tasks in identifying the writer of handwriting, namely identification and verification. Identification task determines the writer of handwriting from many known writers, while verification task determines whether one document and another is written by the same writer.

The challenge in WI is how to acquire the features that reflect the author for these variety styles of handwriting [7], [9], [12], [13], [15], [24], either for one writer or many writers. These features are required to classify in order to identify the variance between features for same writer is lower than different writer which known as Authorship Invarianceness. Among these features are exists the significant individual features which directly unique to those individual.

3 GLOBAL FEATURES REPRESENTATION

In pattern recognition problem, there are many shape representations or description techniques have been explored in order to extract the features from the image. Generally it can be classified into two different approaches when dealing with handwritten word problem, which are analytic (local / structural approach) and holistic (global approach) [26], [27]. For the each approach, it is divided into two method, which are region-based (whole region shape) methods and contour-based (contour only) methods. Holistic approach represent shape as a whole, meanwhile analytic approach represents image in sections. In this work, holistic approach of United Moment Invariant (UMI) is applied in feature extraction task.

Global features extracted with UMI are invariant with respect to all different writing styles. Words in general may be cursive, minor touching discrete, purely discrete, one or two characters are isolated and others are discrete or mixture of these style and it still as one word. Global technique in holistic approach will extract all of these styles for one word as one whole shape. Shape is an important representation of visual image of an object. It is a very powerful feature when it is used in similarity search. Unlike color and texture features, the shape of an object is strongly tied to the object functionality and identity [28]. Furthermore, the use of holistic approach is shown to be very effective in lexicon reduction [29], moreover to increase the accuracy of classification.

3.1 United Moment Invariant Function

Moment Function has been used in diverse fields ranging from mechanics and statistics to pattern recognition and image understanding [30]. The use of moments in image analysis and pattern recognition was inspired by [31] and [32]. [31] first presented a set of seven-tuplet moments that invariant to position, size, and orientation of the image shape. However, there are many research have been done to prove that there were some drawback in the original work by [31] in terms of invariant such as [33], [34], [35], [36], [37], and [39]. All of these researchers proposed their method of moment and tested on feature extraction phase to represents the image.

A good shape descriptor should be able to find perceptually similar shape where it is usually means rotated, translated, scaled and affined transformed shapes. Furthermore, it can tolerate with human beings in comparing the image shapes. Therefore, [39] derived United Moment Invariants (UMI) based on basic scaling transformation by [31] that can be applied in all conditions with a good set of discriminate shapes features. Moreover, UMI never been tested in WI

domain. With the capability of UMI as a good description of image shape, this work is explored its capability of image representation in WI domain.

[39] proposed UMI with mathematically related to GMI by [31] by considering (1) as normalized central moments:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\frac{p+q+2}{2}}}, \quad p+q = 2,3,... \tag{1}$$

and (2) in discrete form. Central and normalized central moments are given as:

$$\mu'_{pq} = \rho^{p+q}\mu_{pq},$$
$$\eta'_{pq} = \rho^{p+q}\eta_{pq} = \frac{\rho^{p+q}}{\mu_{00}^{\frac{p+q+2}{2}}}\mu_{pq}. \tag{2}$$

and improved moment invariant by [40] is given as:

$$\eta'_{pq} = \frac{\mu_{pq}}{\mu_{00}^{p+q+1}} \tag{3}$$

(1) to (3) have the factor μ_{pq}. Eight feature vector derived by [40] are listed below:

$$\theta_1 = \frac{\sqrt{\phi_2}}{\phi_1} \qquad \theta_2 = \frac{\phi_6}{\phi_1\phi_4}$$
$$\theta_3 = \frac{\sqrt{\phi_5}}{\phi_4} \qquad \theta_4 = \frac{\phi_5}{\phi_8\phi_4}$$
$$\theta_5 = \frac{\phi_1\phi_6}{\phi_2\phi_8} \qquad \theta_6 = \left(\phi_1 + \sqrt{\phi_2}\right)\frac{\phi_8}{\phi_6}$$
$$\theta_7 = \frac{\phi_1\phi_5}{\phi_8\phi_6} \qquad \theta_8 = \frac{\phi_8 + \phi_4}{\sqrt{\phi_5}} \tag{4}$$

where ϕ_i are Hu's moment invariants.

4 FEATURE SELECTION

Feature selection has become an active research area for decades, and has been proven in both theory and practice [41]. The main objective of feature selection is to select the minimally sized subset of features as long as the classification accuracy does not significantly decreased and the result of the selected features class distribution is as close as possible to original class distribution [1]. In contrast to other dimensionality reduction methods like those based on projection or compression, feature selection methods do not alter the original representation of the variables, but merely select a subset of them. Thus, they preserve the original semantics of the variables. However, the advantages of feature selection methods come at a certain price, as the search for a subset of relevant features introduces an additional layer of complexity in the modeling task [2]. In this work, feature selection is explored in order to find the most significant features which by is the unique features of individual's writing. The unique features a mainly contribute to the concept of Authorship Invarianceness in WI.

There are three general methods of feature selection which are filter method, wrapper method, and embedded method [42]. Filter method assesses the relevance of features by looking only at the intrinsic properties of the data. A feature relevance score is calculated, and low-scoring features are removed [3]. Simultaneously, wrapper method uses an induction algorithm to estimate the merit of feature subsets. It explores the space of features subsets to optimize the induction algorithm that uses the subset for classification [4]. On the other hand,

in embedded method, the selection process is done inside the induction algorithm itself, being far less computationally intensive compared with wrapper methods [5]. **Figure 1** depicts the model of feature selection methods.

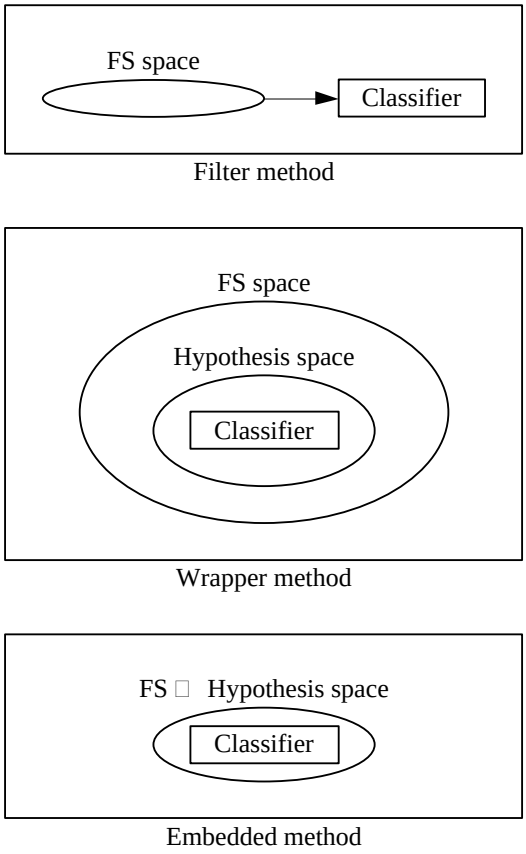

Figure 1. The model of feature selection methods

Studies have shown that there are no feature selection methods more superior compared to others [6]. The selection of the methods to use sometimes depends on the size of the data itself. Using filter methods means to have a good computational complexity, but the higher complexity of the wrapper methods will also produce higher accuracy in the final result, whereas embedded methods are intrinsic to some learning algorithm and so only those algorithm designed with this characteristic can be used.

The focus of this paper, however, is to explore the use of wrapper methods. The rationale for wrapper methods is that the induction method that will ultimately use the feature subset should provide a better estimate of accuracy than a separate measure that has an entirely different inductive bias [3].

The wrapper method is computationally demanding, but often is more accurate. A wrapper algorithm explores the space of features subsets to optimize the induction algorithm that uses the subset for classification. These methods based on penalization face a combinatorial challenge when the set of variables has no specific order and when the search must be done over its subsets since many problems related to feature extraction have been shown to be NP-hard [4].

Advantages of wrapper are it is including the interaction between feature subset search and model selection, and it has the ability to take into account feature dependencies. The drawback of these methods is that they have a higher risk of over-fitting than filter methods and are very computationally intensive, especially if building the classifier has a high computational cost [2]. There are several wrapper methods, however only two methods will be discussed here. These methods are Sequential Forward Selection and Sequential Forward Floating Selection.

Sequential Forward Selection (SFS) is introduced by [43] which proposed the best subset of features Y_0 that is initialized as the empty set. The feature x^+ that gives the highest correct

classification rate $J(Y_k + x^+)$ is added to Y_k at the each step along with the features which already included in Y_k. The process continues until the correct classification rate given by Y_k and each of the features not yet selected does not increase. SFS performs best when the optimal subset has a small number of features. When the search is near the empty set, a large number of states can be potentially evaluated, and towards the full set, the region examined by SFS is narrower since most of the features have already been selected. The algorithm of SFS is shown as below:

1. Start with the empty set $Y_0 = \{\phi\}$
2. Select the next best feature $x^+ = \arg\max_{x^+ \notin Y_k} [J(Y_k + x^+)]$
3. If $J(Y_k + x^+) > J(Y_k)$
3.1. Update $Y_{k+1} = Y_k + x^+; k = k + 1$
3.2. Go to step 2
4. End

However, this method suffers from the nesting effect. This means that a feature that is included in some step of the iterative process cannot be excluded in a later step. Thus, the results are sub-optimal. Therefore, the Sequential Forward Floating Selection (SFFS) method was introduced by [44] to deal with the nesting problem. In SFFS, Y_0 is initialized as the empty set and in each step a new subset is generated first by adding a feature x^+, but after that features x^- is searched for to be eliminated from Y_k until the correct classification rate $J(Y_k - x^-)$ decreases. The iterations continue until no new variable can be added because the recognition rate $J(Y_k + x^+)$ does not increase. The algorithm is as below.

1. Start with the empty set $Y_0 = \{\phi\}$
2. Select the next best feature $x^+ = \arg\max_{x^+ \notin Y_k} [J(Y_k + x^+)]$
3. If $J(Y_k + x^+) > J(Y_k)$
3.1. Update $Y_{k+1} = Y_k + x^+; k = k + 1$
3.2. Remove the worst feature $x^- = \arg\max_{x^- \in Y_k} [J(Y_k - x^-)]$
3.3. If $J(Y_k - x^-) > J(Y_k)$
3.3.1. Update $Y_{k+1} = Y_k - x^-; k = k + 1$
3.3.2. Go to 3.2
3.4. Else
3.4.1. Go to 2
4. End

Most of wrapper methods are constrained by the time complexity, and as the result, its usage is getting less frequent compared to filter method. Thus, an improved wrapper method should be devised to allow faster execution time. Computationally Inexpensive Sequential Forward Floating Selection (CI-SFFS) is introduced as the improvement to SFFS to cater with the slow execution time. The concept of CI-SFFS is similar with traditional SFFS, however it is implemented and enhanced by recent programming techniques, such as memory pooling and multithreading.

The process of searching for the best feature x^+ and the worst feature x^- within SFFS is repetitive, thus making its results are constants, regardless the number of execution. Therefore, it is only efficient if these results are stored in the memory, rather than having to repeat the process and recalculate every result. By storing these results, CI-SFFS only have to determine whether a feature ($x^+ \notin Y_k$) or ($x^- \in Y_k$) has been previously calculated. If it hasn't been calculated, then the result will be

calculated and stored. This process is referred as memory pooling.

Thread is the smallest unit of processing that can be scheduled by an operating system. Multithreading allows multiple threads to exist within the context of a single process [45]. These threads share the process' resources but are able to execute independently.

Threads are divided into two types, user threads and kernel threads. User threads are user-level threads handled independent from and above the kernel and thereby managed without any kernel support. On the other hand, the operating system directly manages the kernel threads. There exist three established multithreading models classifying the form of relationship between user-level and kernel-level threads as one-to-one, many-to-one, and many-to-many [46].

One obvious requirement of multithreading is that the individual threads that make up a process must be switched between at some point. This is necessary because only one thread can have the CPU at a time for execution. Switching between threads can either be cooperative or preemptive [47]. In cooperative task switching, a thread runs until it decides it is done, then lets other threads run, eventually returning to the caller. Preemptive task switching involves a thread that runs until some event (like an interrupt) cause the thread to be suspended and another thread to resume execution.

Multithreading programming benefits [45] are as follow:

1. Improving application responsiveness

Any program in which many activities are not dependent upon each other can be redesigned so that each independent activity is defined as a thread.

2. Using multi-processors efficiently

Applications that express concurrency requirements with threads need not take into account the number of available processors. The performance of the application improves transparently with additional processors because the operating system takes care of scheduling threads for the number of processors that are available.

3. Improving program structure

Many programs are more efficiently structured as multiple independent or semi-independent units of execution instead of as a single, monolithic thread. Multithreaded programs can be more adaptive to variations in user demands than single-threaded programs.

4. Using fewer system resources

Each process has a full address space and operating environment state. Cost of creating and maintaining this large amount of state information makes each process much more expensive than a thread in both time and space. The inherent separation between processes can require a major, including handling communication between the threads in different processes, or synchronizing their actions. When the threads are in the same process, communication and synchronization becomes much easier.

When using the multithreading, the potential challenges it presents must be kept in mind [46]. Some of such challenges are outlined as follow:

1. System calls

One of the issues to keep in mind is how a system call deals with threads contained in a process that is getting duplicated.

2. Cancellations

There are times when it is required to terminate a thread before it completes its purpose, referred to as thread cancellation. When cancelling a thread, there are two approaches available. One is asynchronous cancellation, where one thread terminates another that could lead to orphan resources since the target thread did not have a chance to free them, while in deferred cancellation, each thread keeps checking if it should terminate and if so, do so in an orderly fashion freeing system resources used by the terminating thread.

3. Signal handling

Signals are being used to keep track of events which must follow the same path of execution regardless of their type being synchronous or asynchronous. Some actions produce synchronous signals sent to the causing operation's process. Asynchronous signals are those received as the result of an external event, which are typically sent to another process.

4. Thread pools

Even though creation of threads is more conservative than creating processes, unlimited threads can use up all the resources of a system. This problem can be avoided by having several threads made upon the start of a process and hold them in a pool, where they await task assignment. Once a request is received, it is passed on to an available thread in the pool. Upon completion of the task, the thread then returns to the pool awaiting its next task. If the pool is empty, the system holds the requests until an available thread returned to the pool. This method limits the number of threads in a system to a manageable size, most beneficial when the system does not possess enough resources to handle a high number of threads. In return, the performance of the system increases as thread creation is often slower than reuse of an existing one.

5. Thread-specific data

The sharing of resources of the parent process does benefit multithreading programs, but in cases where a thread may need to hold it's on copy of some data, called thread-specified data; it could be a downfall as well.

Although the time performance is not the primary the consideration in pattern recognition domain, especially in WI, the comparison of time performance between traditional SFFS and CI-SFFS should also be presented in order to justify the quality of the proposed method. **Table 1** shows the average of time performance from five times execution of both wrapper methods.

Table 1. Performance comparison of SFFS and CI-SFFS

Method	Dataset	Subset Length	Evaluated Subset	Processing Time (seconds)
SFFS	Set A	6	64	2199.12
	Set B	5	56	1806.48
	Set C	6	64	2216.11
	Set D	6	64	1756.36
	Set E	5	56	2240.55
	Average	**6**	**61**	**2043.72**
CI-SFFS	Set A	6	20	39.11
	Set B	6	20	39.12
	Set C	6	20	38.36
	Set D	6	20	36.09
	Set E	6	20	38.14
	Average	**6**	**20**	**38.17**

By implementing these recent techniques, it is shown that CI-SFFS produces the output much faster than traditional SFFS (38.17 seconds compared to 2043.72), almost 53.6 times faster. This is because CI-SFFS evaluates lesser number of subset, making it capable to found the most optimal solution much earlier than SFFS, as shown in the number of subset evaluated. The more subset evaluated, the more time consumption is required, and this is because the number of possible subset evaluated is 2^N, where N is the number of features, is directly affecting the time consumption. As mentioned earlier, although time complexity is not an issue in WI domain, faster execution time allows further enhancement to this method, for instance by hybridizing it with recent optimization techniques. The algorithm of CI-SFFS is as shown below:

1. Start with the empty set $Y_0 = \{\phi\}$
2. Calculate the merit of each feature
3. Store the merits in the memory pool
4. Spawn threads of forward feature selector
4.1. Select the next best feature

$$x^+ = \arg\max_{x^+ \notin Y_k} [J(Y_k + x^+)]$$

4.2. If $J(Y_k + x^+) > J(Y_k)$
4.2.1. Update $Y_{k+1} = Y_k + x^+; k = k+1$
4.2.2. Spawn threads of backward feature selector
4.2.2.1. Remove the worst feature

$$x^- = \arg\max_{x^- \in Y_k} [J(Y_k - x^-)]$$

4.2.2.2. If $J(Y_k - x^-) > J(Y_k)$
4.2.2.2.1. Update

$$Y_{k+1} = Y_k - x^-; k = k+1$$

4.2.2.2.2. Go to 4.2.2
4.2.2.3. Else
4.2.2.3.1. Go to 4
4.3. Else
4.3.1. Go to 5
5. End
6.

5 PROPOSED APPROACH

The framework for WI follows the traditional framework of pattern recognition tasks, which are preprocessing, feature extraction, and classification. However, it has been proven that most of preprocessing tasks must be omitted because some of the original and important information are lost, and thus decrease the identification performance in WI domain [48]. **Figure 2** depicts the framework used in the experiment.

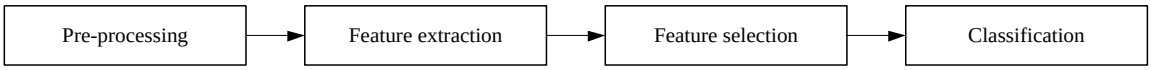

Figure 2. Framework of the experiment

The three commonly used performance measurements for evaluating the performance of feature selection method are number of selected features, classification accuracy, and processing time. However, this research only considers two main measures, which are number of selected features and classification accuracy.

The experiments described in this paper are executed using the IAM database [49]. Various types of word images from IAM database are extracted using UMI to represent the image into feature vector. The selection of significant features using the wrapper methods are performed prior the identification task. The selected features which produce highest accuracy from the identification task are identified as the optimal significant features for WI in this work and also known as unique features of individual's writing.

5.1 Extracting Features

Feature extraction is a process of converting input object into feature vectors. The extracted features are in real value and unique for each word. A set of moments computed from digital image using UMI represents global characteristics of an image shape, and provides a lot of information about different types of geometrical features of the image [50]. Different types of words from IAM database such as 'the', 'and', 'where' and others have been extracted from one author. There are 657 classes available, however only a sample of 60 classes are used for experiments. From these classes, 4400 instances are collected.

One of the usages of UMI in machine learning application is handwriting recognition and handwriting identification. However, handwriting recognition deals with the contents conveyed by the image, while handwriting identification tries to differentiate each image to determine the author of those handwritings. Despite that, both of these tasks embark on the same theoretical foundation.

Extracted features can be divided into micro and macro feature classes which are local and global features. Local features denote the constituent parts of objects and the relationships, meanwhile global features describing properties of the whole object [51]. Good features are those satisfying two requirements which are small intra-class invariance and large inter-class invariance [52]. This can be defined as invarianceness of authorship in WI.

5.2 Selecting Significant Features

Two commonly used wrapper method discussed earlier along with the proposed method will be used to determine the significant features. These feature selection methods will be using Modified Immune Classifier (MIC) [48] as their classifier. Every experiment has been performed using ten-fold cross-validation. These feature selection methods will be executed five times to ensure the performance is stable and accurate.

The uniqueness of this work is to find the significant feature which actually is the unique features of individual's writing. The invarianceness of authorship relates to individuality of handwriting with the unique features of individual's writing. The highest accuracy of selected features proofs the invarianceness of authorship for intra-class is lower than inter-class where each individual's writing contains the unique styles of handwriting that is different with other individual. To achieve this, the process of selecting significant features is carried out using the proposed wrapper method prior to identification task.

The number of features selected by feature selection methods is the primary consideration of this study. Feature selection methods discussed earlier will be used to determine the significant features. In order to justify the quality of feature subset produced by each method, other state-of-the-art feature selection methods are also used, which are Correlation-based Feature Selection (CFS) [3], Consistency-based Feature Selection, also known as Las Vegas Filter (LVF) [54], and Fast Correlation-based Filter (FCBF) [55]. These feature selection methods are provided in WEKA [56]. Justification of these feature selection methods has been presented in [22]. **Table 2** is the result of selection for each feature invariant data set.

Table 2. Experimental Results on Feature Selection.

Method	Execution	Set A	Set B	Set C	Set D	Set E	Intersection
SFS	Execution #1	f2, f3, f6, f8	f2, f3, f4, f6, f8	f1, f3, f6, f7, f8	f3, f6, f8	f1, f2, f3, f5, f6, f7	**f3, f6**
	Execution #2	f1, f3, f4, f6, f8	f1, f3, f4, f5, f6, f8	f1, f3, f4, f6, f8	f1, f2, f3, f6	f1, f3, f6	**f3, f6**
	Execution #3	f2, f3, f4, f5, f6, f8	f1, f3, f6, f7, f8	f1, f3, f6, f8	f2, f3, f6, f7, f8	f3, f4, f5, f6, f7, f8	**f3, f6, f8**
	Execution #4	f2, f3, f6, f8	f1, f3, f4, f5, f6, f8	f1, f2, f3, f4, f5, f6	f1, f3, f4, f5, f6	f1, f3, f6	**f3, f6**
	Execution #5	f3, f6, f7, f8	f1, f2, f3, f6	f2, f3, f4, f5, f6, f7, f8	f1, f3, f6, f8	f2, f3, f6, f8	**f3, f6**
	Intersection	**f3, f6, f8**	**f3, f6**	**f3, f6**	**f3, f6**	**f3, f6**	**f3, f6**
SFFS	Execution #1	f1, f3, f6	f2, f3, f4, f6	f1, f3, f4, f5, f6, f8	f1, f3, f6, f8	f3, f4, f6, f7, f8	**f3, f6**
	Execution #2	f1, f3, f5, f6, f7, f8	f3, f4, f6, f7, f8	f1, f2, f3, f4, f6, f8	f1, f3, f4, f5, f6, f8	f2, f3, f5, f6	**f3, f6**
	Execution #3	f2, f3, f4, f5, f6, f7, f8	f2, f3, f5, f6, f8	f1, f2, f3, f6, f7, f8	f2, f3, f6, f8	f2, f3, f6, f8	**f3, f6, f8**
	Execution #4	f3, f4, f6, f8	f1, f2, f3, f6	f3, f6, f7, f8	f3, f4, f6, f8	f3, f6, f8	**f3, f6**
	Execution #5	f2, f3, f4, f5, f6, f7	f1, f2, f3, f6, f7, f8	f2, f3, f4, f5, f6, f8	f1, f3, f6, f8	f3, f6, f7, f8	**f3, f6**
	Intersection	**f3, f6**	**f3, f6**	**f3, f6, f8**	**f3, f6, f8**	**f3, f6**	**f3, f6**
CI-SFFS	Execution #1	f1, f3, f4, f5, f6, f8	f1, f3, f4, f5, f6, f8	f2, f3, f6, f7, f8	f2, f3, f5, f6	f3, f5, f6, f8	**f3, f6**
	Execution #2	f1, f3, f4, f5, f6, f8	f1, f2, f3, f5, f6	f1, f2, f3, f5, f6	f1, f3, f5, f6	f1, f2, f3, f5, f6	**f3, f6**

Method	Execution	Set A	Set B	Set C	Set D	Set E	Intersection
	Execution #3	f1, f3, f4, f5, f6, f7	f1, f2, f3, f4, f6, f8	f1, f3, f4, f5, f6, f8	f1, f2, f3, f5, f6	f3, f5, f6, f8	**f3, f6**
	Execution #4	f1, f2, f3, f4, f6, f7, f8	f1, f3, f4, f5, f6, f8	f3, f4, f6, f7, f8	f1, f3, f4, f6, f7, f8	f2, f3, f5, f6, f7, f8	**f3, f6, f8**
	Execution #5	f1, f3, f5, f6, f7, f8	f1, f2, f3, f5, f6	f1, f3, f4, f6, f7, f8	f2, f3, f4, f6, f7, f8	f1, f3, f4, f6, f7, f8	**f3, f6**
	Intersection	**f1, f3, f6**	**f1, f3, f6**	**f3, f6**	**f3, f6**	**f3, f6**	**f3, f6**
CFS	Execution #1	f1, f2, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	f1, f3, f4, f5, f6, f7	f1, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	**f1, f3, f5, f7**
	Execution #2	f1, f2, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	f1, f3, f4, f5, f6, f7	f1, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	**f1, f3, f5, f7**
	Execution #3	f1, f2, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	f1, f3, f4, f5, f6, f7	f1, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	**f1, f3, f5, f7**
	Execution #4	f1, f2, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	f1, f3, f4, f5, f6, f7	f1, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	**f1, f3, f5, f7**
	Execution #5	f1, f2, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	f1, f3, f4, f5, f6, f7	f1, f3, f5, f7, f8	f1, f3, f4, f5, f6, f7	**f1, f3, f5, f7**
	Intersection	**f1, f2, f3, f5, f7, f8**	**f1, f3, f4, f5, f6, f7**	**f1, f3, f4, f5, f6, f7**	**f1, f3, f5, f7, f8**	**f1, f3, f4, f5, f6, f7**	**f1, f3, f5, f7**
LVF	Execution #1	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	**f2, f3, f4, f6**
	Execution #2	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	**f2, f3, f4, f6**
	Execution #3	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	**f2, f3, f4, f6**
	Execution #4	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	**f2, f3, f4, f6**
	Execution #5	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	f2, f3, f4, f6	**f2, f3, f4, f6**
	Intersection	**f2, f3, f4, f6**	**f2, f3, f4, f6**	**f2, f3, f4, f6**	**f2, f3, f4, f6**	**f2, f3, f4, f6**	**f2, f3, f4, f6**
FCBF	Execution #1	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	**f1, f2, f3, f4, f5, f6, f7, f8**
	Execution #2	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	**f1, f2, f3, f4, f5, f6, f7, f8**
	Execution #3	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	**f1, f2, f3, f4, f5, f6, f7, f8**
	Execution #4	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	**f1, f2, f3, f4, f5, f6, f7, f8**
	Execution #5	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	f1, f2, f3, f4, f5, f6, f7, f8	**f1, f2, f3, f4, f5, f6, f7, f8**
	Intersection	**f1, f2, f3, f4, f5, f6, f7, f8**	**f1, f2, f3, f4, f5, f6, f7, f8**	**f1, f2, f3, f4, f5, f6, f7, f8**	**f1, f2, f3, f4, f5, f6, f7, f8**	**f1, f2, f3, f4, f5, f6, f7, f8**	**f1, f2, f3, f4, f5, f6, f7, f8**

Based on the feature selection results, it is shown that these feature selection methods yield different subset with different size. It is shown that FCBF is

shown to unable reduce the number of features, this is because this feature selection method is more suitable when handling high-dimensional data, because it analyze the correlation between features, which is feature relevancy and feature redundancy. Thus, this method will perform poorly when it failed to find the correlation between features, or they overestimate the correlation between features. In other domain of pattern recognition, the result obtained from FCBF can be considered as suboptimal result, however in this WI domain, this feature selection method is still considered to achieve the purpose of the experiment. This is because the purpose of feature selection in WI is not only to reduce the number of features; instead it is to determine the most significant features (unique features). Thus, FCBF considers all features are significant.

On the contrary, the rest of the methods (CFS, LVF, SFS, SFFS and CI-SFFS) are able to identify the significant features. It should be noted that the number of features selected is not always an indicator of a successful feature selection process. Therefore, further validation to justify the result produced by these methods must be designed, which is the classification accuracy.

It is also worth mentioning that although these feature selection methods yield different result with different size, they seem to always include the third feature (f3) in their results. Therefore, it can be concluded that the third feature (f3) is the most significant feature, and it is chosen as significant unique feature in order to proof the invarianceness of authorship in this work.

5.3 Identifying the Authorship using Significant Features

The second measurement of this study is classification accuracy. The selected significant features from every feature selection methods must be justified and validated through identification performance. In order to justify the quality of feature subset produced by each method, the feature subsets are tested against classification, which uses MIC as the classifier. All of these methods are both capable to identify the most significant features and at the same time they validate the invarianceness of authorship concept where the invariance between features for intra-class is lower than inter-class. This conforms the significant features is relate to invarianceness of authorship on WI. **Table 3** is the result of identification accuracy for each feature subset.

Table 3. Experimental Results on Identification Accuracy (%).

Method	Execution	Set A	Set B	Set C	Set D	Set E	Average
SFS	Execution #1	97.40	97.18	96.92	96.14	96.94	**96.92**
	Execution #2	97.29	97.77	96.01	96.47	95.80	**96.67**
	Execution #3	97.63	97.30	95.78	96.80	97.05	**96.91**
	Execution #4	97.40	97.77	97.26	96.80	95.80	**97.01**
	Execution #5	97.51	96.59	97.38	96.14	96.49	**96.82**
	Average	**97.45**	**97.32**	**96.67**	**96.47**	**96.42**	**96.87**
SFFS	Execution #1	96.95	96.71	97.04	96.14	96.49	**96.66**
	Execution #2	97.40	97.18	96.58	97.13	96.94	**97.05**
	Execution #3	94.35	97.41	97.04	96.03	96.49	**96.26**
	Execution #4	97.06	96.59	96.58	96.14	96.03	**96.48**

Method	Execution	Set A	Set B	Set C	Set D	Set E	Average
	Execution #5	97.51	97.18	97.04	96.14	96.60	**96.89**
	Average	**96.66**	**97.02**	**96.85**	**96.32**	**96.51**	**96.67**
CI-SFFS	Execution #1	97.97	97.89	97.15	96.80	96.83	**97.33**
	Execution #2	97.85	97.06	97.26	96.91	97.17	**97.25**
	Execution #3	97.85	97.42	97.61	96.91	96.83	**97.32**
	Execution #4	97.97	97.89	96.92	97.13	97.39	**97.46**
	Execution #5	97.97	97.06	97.04	97.13	96.94	**97.23**
	Average	**97.92**	**97.46**	**97.19**	**96.98**	**97.03**	**97.32**
CFS	Execution #1	94.24	97.18	97.18	94.01	97.18	**95.95**
	Execution #2	94.24	97.18	97.18	94.01	97.18	**95.95**
	Execution #3	94.24	97.18	97.18	94.01	97.18	**95.95**
	Execution #4	94.24	97.18	97.18	94.01	97.18	**95.95**
	Execution #5	94.24	97.18	97.18	94.01	97.18	**95.95**
	Average	**94.24**	**97.18**	**97.18**	**94.01**	**97.18**	**95.95**
LVF	Execution #1	97.40	97.40	97.40	97.40	97.40	**97.40**
	Execution #2	97.40	97.40	97.40	97.40	97.40	**97.40**
	Execution #3	97.40	97.40	97.40	97.40	97.40	**97.40**
	Execution #4	97.40	97.40	97.40	97.40	97.40	**97.40**
	Execution #5	97.40	97.40	97.40	97.40	97.40	**97.40**
	Average	**97.40**	**97.40**	**97.40**	**97.40**	**97.40**	**97.40**
FCBF	Execution #1	97.74	97.74	97.74	97.74	97.74	**97.74**
	Execution #2	97.74	97.74	97.74	97.74	97.74	**97.74**
	Execution #3	97.74	97.74	97.74	97.74	97.74	**97.74**
	Execution #4	97.74	97.74	97.74	97.74	97.74	**97.74**
	Execution #5	97.74	97.74	97.74	97.74	97.74	**97.74**
	Average	**97.74**	**97.74**	**97.74**	**97.74**	**97.74**	**97.74**

Based on the results, the accuracy is at its highest when the number of features is between 4-7 features. It is shown that FCBF produces the best accuracy (97.87%) and equal with the original dataset performance (97.87%). However, the number of features produced by FCBF is equal with the actual set (8 features). Meaning that, FCBF needs all features to produce the best performance.

The second best accuracy is LVF (97.40%). The results of LVF are shown to be stable, regardless of dataset and the number of execution. This is because the nature of the data that is consistent allows LVF to perform well. The next best accuracy is produced by CI-SFFS (97.32%). It is proven that although the time complexity has been greatly reduced, the classification accuracy has not been deteriorating; instead it is outperforming the classification accuracy of its predecessor (SFFS).

On the other hand, both SFS (96.87%) and SFFS (96.67%) with lower number of features still can obtain almost similar performance, although it is slightly lower than original dataset (97.74%). These feature selection methods outperform CFS. This is due to the behavior of these methods which can specifically identify the unique features in dataset, therefore it is resulting the highest performance. Besides that, the wrapper method is able to recognize importance of each feature in every iteration.

These methods are both capable to identify the most significant features and at the same time they validate the

invarianceness of authorship concept where the invariance between features for intra-class is lower than inter-class. As a normal practice in pattern recognition, it can be achieved by calculating the invariance for intra-class and inter-class using Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - r_i\right|. \qquad (5)$$

The result in **Table 4** shows that the invarianceness of authorship is proven where the invarianceness between features using selected features for intra-class (same author) is smaller compared to inter-class (different author). This conforms the significant features is relate to invarianceness of authorship on WI.

Table 4. Identification Accuracy Results (%).

Various words	1 writer	10 writers	20 writers
20 words	0.278666	0.295112	0.524758
40 words	0.289052	0.295236	0.512279
60 words	0.282408	0.293509	0.527289
80 words	0.270236	0.3018	0.520221
100 words	0.281886	0.355219	0.544051

It is also shown that CFS is also capable to obtain good result (95.95%), although it is not as good as LVF, SFS and SFFS. Although FCBF is the enhancement of CFS, it is shown that CFS is still better than FCBF in some dataset. This is because FCBF determines the correlation between features faster than CFS, which may causing the method to overestimate the correlation between features, thus causing it to select all the features.

6 CONCLUSION AND FUTURE WORK

An improved sequential forward floating selection, Computationally Inexpensive Sequential Forward Floating Selection (CI-SFFS), has been developed to better adapt the nature of the data, and thus increase the performance of state-of-the-art wrapper feature selection method SFFS. The exploration of significant unique features relates to authorship invarianceness has been presented in this paper. A scientific validation has been provided as evidence of significant features can be used to proof the authorship invarianceness in WI. In future works, the selected unique features will be further explored with other classifier to confirm these features can be used as optimized features with higher accuracy. Future works to hybridize the proposed feature selection method with recent optimization techniques is also required. This is to allow better performance of the proposed method.

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