

Heuristics for The Whitehead Minimization Problem

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Abstract

In this paper we discuss several heuristic strategies which allow one to solve the Whitehead's minimization problem much faster (on most inputs) than the classical Whitehead algorithm. The mere fact that these strategies work in practice leads to several interesting mathematical conjectures. In particular, we conjecture that the length of most non-minimal elements in a free group can be reduced by a Nielsen automorphism which can be identified by inspecting the structure of the corresponding Whitehead Graph.

1 Introduction to Whitehead method

Let $X = \{x_1, \dots, x_m\}$ be a finite alphabet, $X^{-1} = \{x^{-1} \mid x \in X\}$ be the set of formal inverses of letters from X and $X^{\pm 1} = X \cup X^{-1}$. A word $w = y_1 \dots y_n$ in the alphabet $X^{\pm 1}$ is called *reduced* if $y_i \neq y_{i+1}$ for $i = 1, \dots, n-1$ (here we assume that $(x^{-1})^{-1} = x$). Applying reduction rules $xx^{-1} \rightarrow \varepsilon, x^{-1}x \rightarrow \varepsilon$ (where ε is the empty word), one can reduce each word w in the alphabet $X^{\pm 1}$ to a reduced word \bar{w} . The word \bar{w} is uniquely defined and does not depend on a particular sequence of reductions. Denote by $F = F(X)$ the set of reduced words over $X^{\pm 1}$. The set F forms a group with respect to the multiplication $u \cdot v = \overline{uv}$, which is called a *free* group with *basis* X . The cardinality $|X|$ is called the *rank* of $F(X)$. Sometimes we write F_n instead of F to indicate that the rank of F is equal to n .

A bijection $\phi : F \rightarrow F$ is called an *automorphism* of F if $\phi(uv) = \phi(u)\phi(v)$ for every $u, v \in F$. The set $Aut(F)$ of all automorphisms of F forms a group with respect to composition of maps. Every automorphism $\phi \in Aut(F)$ is completely determined by the images $\phi(x)$ of elements $x \in X$. The following two subsets of $Aut(F)$ play an important part in group theory and topology.

An automorphism $t \in Aut(F)$ is called a *Nielsen automorphism* if for some $x \in X$ t fixes all elements $y \in X, y \neq x$ and maps x to one of the elements $x^{-1}, y^{\pm 1}x, xy^{\pm 1}$. By $N(X)$ we denote the set of all Nielsen automorphisms of F .

An automorphism $t \in Aut(F)$ is called a *Whitehead automorphism* if either t permutes elements of $X^{\pm 1}$ or t fixes a given element $a \in X^{\pm 1}$ and maps

each element $x \in X^{\pm 1}, x \neq a^{\pm 1}$ to one of the elements $x, xa, a^{-1}x$, or $a^{-1}xa$. Obviously, every Nielsen automorphism is also a Whitehead automorphism. By $W(X)$ we denote the set of non-trivial Whitehead's automorphisms of the second type.

Observe that

$$|N(X)| = 4n(n-1), \quad |W(X)| = 2n4^{(n-1)} - 2n$$

where $n = |X|$ is the rank of F .

It is known [4] that every automorphism from $Aut(F)$ is a product of finitely many Nielsen (hence Whitehead) automorphisms.

The automorphic orbit $Orb(w)$ of a word $w \in F$ is the set of all automorphic images of w in F :

$$Orb(w) = \{v \in F \mid \exists \varphi \in Aut(F) \text{ such that } w^\varphi = v\}.$$

A word $w \in F$ is called *minimal* (or *automorphically minimal*) if $|w| \leq |w^\varphi|$ for any $\varphi \in Aut(F)$. By w_{min} we denote a word of minimal length in $Orb(w)$. Notice that w_{min} is not unique.

Problem 1.1 (Minimization Problem (MP)) *For a word $u \in F$ find an automorphism $\varphi \in Aut(F)$ such that $u\varphi = u_{min}$.*

In 1936 J. H. C. Whitehead proved the following result which gives a solution to the minimization problem [7].

Theorem 1.1 (Whitehead) *Let $u, v \in F_n(X)$ and $v \in Orb(u)$. If $|u| > |v|$, then there exists $t \in W(X)$ such that*

$$|u| > |ut|.$$

An automorphism $\phi \in Aut(F)$ is called a length-reducing automorphism for a given word $u \in F$ if $|u\phi| < |u|$. The theorem above claims that the finite set $W(X)$ contains a length-reducing automorphism for every non-minimal word $u \in F$. This allows one to design a simple search algorithm for (MP).

Let $u \in F$. For each $t \in W(X)$ compute the length of the tuple ut until $|u| > |ut|$, then put $t_1 = t, u_1 = ut_1$. Otherwise stop and output $u_{min} = u$. The procedure above is called the *Whitehead Length Reduction routine* (WLR). Now Whitehead Reduction Algorithm (WRA) proceeds as follows. Repeat WLR on u , and then on u_1 , and so on, until on some step k WLR gives an output u_{min} . Then $ut_1 \dots t_{k-1} = u_{min}$, so $\phi = t_1 \dots t_{k-1}$ is a required automorphism.

Notice, that the iteration procedure WRA simulates the classical greedy descent method (t_1 is a successful direction from u , t_2 is a successful direction from u_1 , and etc.). Theorem 1.1 guarantees that the greedy approach will always converge to the global minimum.

Clearly, there could be at most $|u|$ repetitions of WLR on an input $u \in F$

$$|u| > |ut_1| > \dots > |ut_1 \dots t_l| = u_{min}, \quad l \leq |u|.$$

Hence the worst case complexity of the algorithm WRA is bounded from above by

$$cA_n|u|^2,$$

where $A_n = 2n4^{(n-1)} - 2n$ is the number of Whitehead automorphisms in $W(X)$. Therefore, in the worst case scenario, the algorithm seems to be impractical for free groups with large ranks. One can try to improve on the number of steps which takes to find a length-reducing automorphism for a given non-minimal element from F . In this context the main question of interest is the complexity of the following

Problem 1.2 (Length Reduction Problem) *For a given non-minimal element $u \in F$ find a length-reducing automorphism.*

We refer to [5] for a general discussion on this problem.

In the next section we give some empirical evidence that using smart strategies in selecting Whitehead automorphisms $t \in W(X)$ one can dramatically improve the average complexity of WRA in terms of the rank of a group.

2 Heuristics for Length Reduction Problem

2.1 Nielsen first

The first heuristic comes from a very naive approach: replace $W(X)$ by $N(X)$ in the Whitehead length reduction routine WLR and denote the resulting routine by NLR. Since the size of $N(X)$ is quadratic and the size of $W(X)$ is exponential in the rank of F , the algorithm NRA may give a real speedup in computations. However, it is known (see [4]) that the Whitehead theorem above does not hold after replacement of $W(X)$ by $N(X)$. Therefore, the algorithm NRA will not give the correct answer at least on some inputs. But this is not the end of the story. Now the question is *how often the length reduction routine NLR gives the correct answer?*

To get some insights, we perform a simple experiment. For free groups F_3 , F_4 and F_5 we generate test sets of non-minimal elements of Whitehead Complexity 1 (see definitions in [5]), described in Table 1. For a detailed description of the data generation procedures we refer to [3].

Dataset	Group	Dataset Size	Min. length	Avg. length	Max. length
D_3	F_3	10143	3	558.2	1306
D_4	F_4	10176	4	570.9	1366
D_5	F_5	10165	5	581.3	1388

Table 1: Statistics of sets of non-minimal elements.

For each set D_n we compute the fraction of elements from D_n which have length-reducing Nielsen automorphisms. The results of the computations together with the corresponding 95% confidence intervals are given in Table 2.

We can see that most of the words have been reduced by Nielsen automorphisms. We would like to mention here, that it can be shown statistically that increasing the length of elements in the datasets does not significantly change the results of experiments.

Dataset	D_3	D_4	D_5
Fraction	0.998	0.997	0.998
95% Conf. Interval	[0.9970,0.9988]	[0.9957,0.9979]	[0.9970,0.9988]

Table 2: Fraction of elements in the sets D_3 , D_4 and D_5 with length-reducing Nielsen automorphisms.

Based on these experiments one can speculate that with very high probability Nielsen automorphisms reduce the length of a given non-minimal element in F . More precisely, we state the following

Conjecture 2.1 *Let U_n be the set of all non-minimal elements in F of length n and $NU_n \subset U_n$ the subset of elements which have Nielsen length-reducing automorphisms. Then*

$$\lim_{n \rightarrow \infty} \frac{|NU_n|}{|U_n|} = 1.$$

Our first heuristic is based on this conjecture and simply suggests to try Nielsen automorphisms first in the routine WLR, i.e., in this case we assume that in the fixed listing of automorphisms of $W(X)$ the automorphism from $N(X)$ come first. We refer to this heuristic as to *Nielsen First* and denote the corresponding Length Reduction Routine and the Whitehead Reduction algorithm (with respect to this ordering of $W(X)$) by WLR_{NF} and WRA_{NF} .

The expected value of the number of steps for the routine WLR_{NF} to find a length-reducing automorphism on an input $u \in F$ of length n is equal to

$$P_n |N(X)| + (1 - P_n)(|W(X)| - |N(X)|),$$

where $P_n = NU_n/U_n$.

Given that Conjecture 2.1 is true, we expect WRA_{NF} to perform much better on average. In the next section we describe experimental results supporting this strategy.

2.2 Cluster analysis

According to the heuristic NF one has to apply Nielsen automorphisms to a given input w in some fixed order, which is independent of the word w . Intuitively, we expect some automorphisms to be more likely to reduce the length of a given word than the others. It suggests that the conditional probabilities

$$Prob(|wt| < |w| \mid w), \quad t \in N(X)$$

may not be equal for different non-minimal words $w \in F$, so the order in which Nielsen automorphisms are applied to an input w should depend on the word w itself.

The question we would like to address next is whether it is possible to find a dependence between a non-minimal word w and its length-reducing Nielsen automorphisms. For this purpose we employ methods from *Statistical Pattern Recognition*.

Briefly, Pattern Recognition aims to classify a variety of given objects into categories based on the existing statistical information. The objects are typically presented by collections of measurements or observations (called *features*) which are real numbers. In this event the tuple of features that corresponds to a given object is called a *feature vector*, it can be viewed as a point in the appropriate multidimensional vector space \mathbb{R}^d . Most of the approaches in Statistical pattern recognition are based on statistical characterizations of features, assuming that objects are generated by a probabilistic system. The detailed description of Pattern Recognition methods is out of scope of this report. We refer interested readers to [1, 2, 6] for general introduction to the subject, and [3] for applications of pattern recognition methods in groups.

Unsupervised learning or *clustering* methods of pattern recognition are used when no a priori information about the objects is available. In this case there are general algorithms to group the feature vectors of objects into some "natural classes" (called *clusters*) relative to the specified similarity assumptions. Intuitively, the objects whose feature vectors belong to the same cluster are more similar to each other than the objects with the feature vectors in different clusters.

The most simple and widely used clustering scheme is called *K-means*. It is an iterative method. Let $D = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$ be a set of given objects, represented by the corresponding feature vectors $\mathbf{x} \in \mathbb{R}^d$. *K-means* begins with a set of K randomly chosen cluster centers $\mu_1^0, \dots, \mu_K^0 \in \mathbb{R}^d$. At iteration i each feature vector is assigned to the nearest cluster center (in some metric $\|\cdot\|$ on \mathbb{R}^d). This forms the cluster sets C_1^i, \dots, C_K^i , where

$$C_j^i = \{\mathbf{x} \mid \|\mathbf{x} - \mu_j^i\| \leq \|\mathbf{x} - \mu_m^i\|, \mathbf{x} \in D, m = 1, \dots, K\}.$$

Then each cluster center is redefined as the mean of the feature vectors assigned to the cluster:

$$\mu_k^{i+1} = \frac{1}{|C_k^i|} \sum_{\mathbf{x} \in C_k^i} \mathbf{x}.$$

Each iteration reduces the criterion function J^i defined as

$$J^i = \sum_{k=1}^K \sum_{\mathbf{x} \in C_k^i} \|\mathbf{x} - \mu_k^i\|.$$

As this criterion function is bounded below by zero, the iterations must

converge. This method works well when clusters are mutually exclusive and compact around their center means.

Here we claim that K -means algorithm allows one to discover some natural classes of non-minimal words. We show below that analysis of the corresponding cluster structures sheds some light on the relation between non-minimal words and their length-reducing automorphisms.

We define features of elements $w \in F(X)$ as follows. Recall that the Labelled Whitehead Graph $WG(w) = (V, E)$ of an element $w \in F(X)$ is a weighted non-oriented graph, where the set of vertices V is equal to the set $X^{\pm 1}$, and for $x_i, x_j \in X^{\pm 1}$ there is an edge $(x_i, x_j) \in E$ if the subword $x_i x_j^{-1}$ (or $x_j x_i^{-1}$) occurs in the word w viewed as a cyclic word. Every edge (x_i, x_j) is assigned a weight l_{ij} which is the number of times the subwords $x_i x_j^{-1}$ and $x_j x_i^{-1}$ occur in w .

Let $l(w)$ be a vector of edge weights in the Whitehead Graph $WG(w)$ with respect to a fixed order. We define a feature vector $f(w)$ by

$$f(w) = \frac{1}{|w|} l(w).$$

To execute the K -means algorithm one has to define in advance the expected number of clusters K . Since we would like these clusters to be related to the set of Nielsen automorphisms $N(X)$ we put $K = |N(X)|$.

To evaluate usefulness of the clustering we use the goodness measure R_{max} defined below. Let $\mathcal{C} \subset D$ be a cluster of the data set $D \subset F_n = F(X)$. For $t \in N(X)$ define

$$R(t, \mathcal{C}) = \frac{|\{w \in \mathcal{C} \mid |wt| < |w|\}|}{|\mathcal{C}|}.$$

The number $R(t, \mathcal{C})$ shows how many elements in \mathcal{C} are reducible by t . Now put

$$R_{max}(\mathcal{C}) = \max\{R(t, \mathcal{C}) \mid t \in N(X)\}$$

and denote by $t_{\mathcal{C}}$ a Nielsen automorphism $t \in N(X)$ such that $R(t_{\mathcal{C}}, \mathcal{C}) = R_{max}(\mathcal{C})$. The number $R_{max}(\mathcal{C})$ shows how many elements in \mathcal{C} can be reduced by a single automorphism, in this case by $t_{\mathcal{C}}$. We also define the average value of the goodness measure

$$avg(R_{max}) = \frac{1}{K} \sum_{i=1}^K R_{max}(\mathcal{C}_i),$$

where K is the number of clusters.

The results of K -mean cluster analysis of sets of randomly generated non-minimal elements in free groups F_3, F_4, F_5 are given in Table 3. It shows that more than 70% of elements in every cluster can be reduced by the same Nielsen automorphism. In the free group F_3 , where the number of clusters is significantly smaller, the corresponding percentage is over 98%. Moreover, our experiments show that $t_{\mathcal{C}_i} \neq t_{\mathcal{C}_j}$ for $i \neq j$. In other words there are no two distinct clusters

Free group	F_3	F_4	F_5
number of clusters, K	24	48	80
$avg(R_{max}), K$ -means	0.985	0.879	0.731

Table 3: Average values of the goodness measure R_{max} for K -means clustering.

such that one and the same Nielsen automorphism reduces most of the elements in both clusters.

The discovered cluster structure gives rise to the following strategy in solving the Length Reduction Problem for a given word w . Let μ_1, \dots, μ_K be the centers of clusters $\mathcal{C}_1, \dots, \mathcal{C}_K$ computed by the K -means procedure. We compute the distance $\|f(w) - \mu_i\|$ for each $i = 1, \dots, K$. Now we list the Nielsen automorphisms in $N(X)$ in the order $t_{i_1}, t_{i_2}, \dots, t_{i_K}$ with respect to the distances

$$\|f(w) - \mu_{i_1}\| \leq \|f(w) - \mu_{i_2}\| \leq \dots \leq \|f(w) - \mu_{i_K}\|.$$

To find a length reducing automorphism for a given word w we subsequently apply automorphisms from $N(X)$ in the prescribed order until we find an automorphism $t_i \in N(X)$ which reduces the length of w . If such an automorphism does not exist we proceed with the remaining automorphisms from $W(X) - N(X)$ as in the NF heuristic.

From the description of the K -means method we know that clusters are characterized by the center means of the feature vectors of elements in the same cluster. The observations above lead us to the following vaguely stated conjecture, which gives a model to describe behavior of non-minimal elements from F in terms of their feature vectors.

Conjecture 2.2 *The feature vectors of weights of the Whitehead Graphs of elements from F are separated into bounded regions in the corresponding space. Each such region can be bounded by a hypersurface and corresponds to a particular Nielsen automorphism in a sense that all elements in the corresponding class can be reduced by that automorphism.*

2.3 Improvement on the clustering

Experiments with K -means clustering algorithm show that clustering is a useful tool in solving the length reduction problem. Now, the goal is to make clustering more effective. The further analysis of the clusters suggests that to some extent they correspond to partitions of elements in F which can be reduced by one and only one Nielsen automorphism. To verify this conjecture we perform the following experiment.

Let $S \subset F_n = F(X)$ be a set of randomly generated non-minimal elements and D the set used for cluster analysis in the previous section. Note that S is generated independently from the set D . For each automorphism $t \in N(X)$ put

$$O_t = \{w \in S \mid \forall r \in N(X)(|wr| < |w| \iff r = t)\}$$

and define new cluster centers by

$$\lambda_t = \frac{1}{|O_t|} \sum_{w \in O_t} f(w) \quad (1)$$

as the mean feature vector of the elements from S that can be reduced only by t and no other automorphisms.

We cluster elements from D based on the distance between the corresponding feature vector and centers λ_t :

$$\mathcal{C}_t = \{w \in D \mid \forall r \in N(X) (\|f(w) - \lambda_t\| \leq \|f(w) - \lambda_r\|)\}.$$

The results of evaluation of the clusters \mathcal{C}_t are given in Table 4. One can see that the goodness measure is improved and is close to 1 in every case.

Free group	F_3	F_4	F_5
number of clusters, K	24	48	80
$avg(R_{max})$, distance to λ_t	0.998	0.993	0.991

Table 4: Average values of the goodness measure R_{max} for the clustering based on the distance to the estimated centers λ_t .

Similar to the strategy based on the centers of the K -means clusters, we define a new search procedure WRA_C which employs a heuristic based on the distances to centers λ_t . Let w be a word and $\langle \lambda_{t_1}, \dots, \lambda_{t_K} \rangle$ be the centers corresponding to each of the Nielsen automorphisms $t_i \in N(X)$. Put $d(i) = \|f(w) - \lambda_{t_i}\|$ and construct a vector

$$\langle d(m_1), d(m_2), \dots, d(m_K) \rangle,$$

where

$$d(m_1) \leq d(m_2) \leq \dots \leq d(m_K).$$

To find a length reducing automorphism for a given word w , the algorithm WRA_C applies Whitehead automorphisms to w in the following order. First, Nielsen automorphisms t_{m_1}, \dots, t_{m_K} are applied subsequently. If none of the Nielsen automorphisms reduces the length of w the algorithm WRA_C proceed with the remaining automorphisms $W(X) - N(X)$ in some fixed order.

Based on the results of the cluster analysis from Table 4, we expect the algorithm WRA_C to reduce a non-minimal word w using very few elementary automorphisms on average.

2.4 Maximal weight edges

Now we would like to take a closer look at the edges' weight distributions at the cluster centers. First, observe that every edge in the Whitehead graph WG , except for the ones which correspond to subwords of type x^2 , $x \in X^{\pm 1}$, will

correspond to subwords reducible by two particular Nielsen transformations. For example, edge connecting nodes a and b corresponds to subwords $(ab^{-1})^{\pm 1}$ both of which are reduced by automorphisms

$$(a \rightarrow ab, b \rightarrow b),$$

$$(a \rightarrow a, b \rightarrow ba).$$

In fact there is no other Nielsen transformation that will reduce the length of words $(ab^{-1})^{\pm 1}$.

To generalize, let $WG(w)$ be a Whitehead graph of a word w with the vertex set V and the set of edges E . Let $e = (x, y^{-1})$, $x, y^{-1} \in V$, be an edge in E . By construction e corresponds to subwords $s_e = (xy)^{\pm 1}$ of the word w . The only Nielsen automorphisms which reduce length of the subwords s_e are

$$\psi_e^x : x \rightarrow xy^{-1}, z \rightarrow z, \forall z \neq x, z \in X$$

and

$$\psi_e^y : y \rightarrow x^{-1}y, z \rightarrow z, \forall z \neq y, z \in X.$$

We will call automorphisms ψ_e^x, ψ_e^y the length reducing Nielsen automorphisms with respect to the edge $e = (x, y^{-1})$ and denote $\psi_e = \{\psi_e^x, \psi_e^y\}$.

The following phenomenon has been observed for all clusters in free groups F_3, F_4 , and F_5 . Let C_t be a cluster of a test set D_n , $n = 3, 4, 5$, then for all $t \in N(X)$,

$$t \in \psi_{e_{max}},$$

where e_{max} is the edge having the maximal weight in the cluster center λ_t . It suggests that at least in the case of free groups F_3, F_4, F_5 one can try to estimate a length-reducing automorphism for given word w by taking the length-reducing Nielsen automorphisms of the highest weight edge in the Whitehead graph $WG(w)$.

To evaluate the goodness of the heuristic based on the maximal edge weight in the Whitehead graph we compute the fraction of elements in the sets D_3, D_4 and D_5 , reducible by the Nielsen automorphisms corresponding to the maximal weight edge. The corresponding goodness measure, evaluated on a set D , is given by

$$\mathcal{G}_{MAX} = \frac{1}{|D|} |\{w \in D \mid \exists t \in \psi_{e_{max}(w)}, \text{ s.t. } |wt| < |w|\}|.$$

Dataset	D_3	D_4	D_5
\mathcal{G}_{MAX}	0.991	0.986	0.986

Table 5: Values of the goodness measure \mathcal{G}_{MAX} for sets of non-minimal elements in free groups F_3, F_4 and F_5 .

Values of the goodness measure \mathcal{G}_{MAX} for test sets in free groups F_3 , F_4 and F_5 are given in Table 5. It shows, that heuristic is surprisingly effective. Nevertheless, centroid based method still yields better results. Note that \mathcal{G}_{MAX} measures success of applying two automorphisms corresponding to the maximal weight edge, where the centroid based method was evaluated by the success rate of only one automorphism which corresponds to the closest center.

The observation provides a new search procedure which we denote by WRA_{MAX} . Let w be a word and $WG(w) = (V, E)$ be the corresponding Whitehead graph. Denote by E' the set of edges which do not correspond to the subwords of type $x^{\pm 2}$, $x \in X$

$$E' = \{e \in E \mid e \neq (v, v^{-1}), v \in V\}.$$

It has been shown above, that for each edge e from E' there exists two unique length reducing automorphisms. Note that $2|E'| = |N(X)|$, where $N(X)$ is the set of Nielsen automorphisms for free group $F(X)$.

We can order Nielsen automorphisms $\psi_{e_i} \subset N(X)$:

$$\langle \psi_{e_1}, \psi_{e_2}, \dots, \psi_{e_{|E'|}} \rangle \quad (2)$$

such that edges $e_1, \dots, e_{|E'|}$ are chosen according to the decreasing order of the values of the corresponding weights

$$\omega_{e_1} \geq \omega_{e_2} \geq \dots \geq \omega_{e_{|E'|}}.$$

Note that ψ_e is not a single automorphism, but a pair of Nielsen length reducing automorphisms with respect to the edge e . Here we do not give any preference in ordering automorphisms in ψ_e .

To find a length-reducing automorphism for w procedure WRA_{MAX} first applies Nielsen automorphisms in the order given by (2). If none of the Nielsen automorphisms reduces the length of w , WRA_{MAX} proceeds with the remaining automorphisms from $W(X) - N(X)$.

3 Comparison of the strategies

In this section we describe experiments designed to compare the performance of WRA implemented with different search strategies. We compare four variations of the algorithm. WRA_R is the variation of WRA, where a random order of the elements from W_n is used when searching for a length reducing automorphisms. WRA_{NF} and WRA_C correspond to the implementations with Nielsen First and Centroid based heuristics respectively. The algorithm WRA_{MAX} employs strategy which applies automorphisms corresponding to the largest edge weights of the Whitehead Graph. The algorithms were compared on randomly generated sets of primitive elements S_3 , S_4 , S_5 in free groups F_3 , F_4 , and F_5 , respectively. Some descriptive statistics of the test sets S_n are given in Table 6.

Let \mathcal{A} be one of the variations WRA_R , WRA_{NF} , WRA_C , and WRA_{MAX} of the Whitehead Reduction Algorithm. By an elementary step of the algorithm \mathcal{A} we mean one application of a Whitehead automorphism to a given word. Below

Dataset	Group	Dataset Size	Min. length	Avg. length	Max. length
S_3	F_3	5645	3	1422.1	143020
S_4	F_4	5241	4	2513.1	168353
S_5	F_5	3821	5	2430.5	160794

Table 6: Statistics of the test sets of primitive elements.

we evaluate the performance of \mathcal{A} with respect to the number of elementary steps that are required by \mathcal{A} to execute a particular routine.

Let $N_{total} = N_{total}(\mathcal{A}, S_n)$ be the average of the total number of elementary steps required by \mathcal{A} to reduce a given primitive element $w \in S_n$ to a generator.

By $N_{red} = N_{red}(\mathcal{A}, S_n)$ we denote the average number of elementary length-reducing steps required by \mathcal{A} to reduce a given primitive element $w \in S_n$ to a generator, so N_{red} is the average number of "productive" steps performed by \mathcal{A} . It follows that if t_1, \dots, t_l are all the length reducing automorphisms found by \mathcal{A} when executing its routine on an input $w \in S_n$ then $|wt_1 \dots t_l| = 1$ and the average value of l is equal to N_{red} .

Finally, denote by $N_{LRP} = N_{LRP}(\mathcal{A}, S_n)$ the average number of elementary steps required by \mathcal{A} to find a length-reducing automorphism for a given non-minimal input w .

In Table 7 we present results of our experiments on performance of the algorithms WRA_R , WRA_{NF} , WRA_C and WRA_{MAX} on the test sets S_n , $n = 3, 4, 5$. The algorithms compare as expected. The algorithms WRA_C and WRA_{MAX} perform very efficiently with the numbers N_{LRP} and N_{red} being small. Algorithm WRA_C based on the centroid approach shows best over all performance. The growth of the numbers N_{LRP} with the rank could be explained by occasional occurrence of non-minimal words that cannot be reduced by Nielsen automorphisms. In this event the algorithm tries Whitehead automorphisms from $W(X) - N(X)$ the number of which growth exponentially with the rank. Notice that in every our experiment the number N_{red} of length reductions performed by WRA_C is less than the corresponding number in the other approaches.

In Table 8 we give the correlation coefficients showing dependence of the number of elementary steps required by a particular algorithm to find a length-reducing automorphism with respect to the length of the input words. The coefficients are negative in all cases which indicates that the values of N_{LRP} do not increase when the words' length increases.

4 Conclusions

The experimental results presented in this paper show that using appropriate heuristics in the algorithm WRA, one can significantly reduce the complexity of the Whitehead minimization problem on most inputs with respect to the group rank. Suggested heuristics reduce the average number of Whitehead automorphisms required to find a length-reducing automorphism for a given

Strategy	N_{total}	N_{red}	N_{LRP}
WRA_C	19.9	18.4	1.1
WRA_{MAX}	47.1	23.9	1.9
WRA_{NF}	207.8	28.2	7.37
WRA_R	374.8	29.8	12.6

a) F_3 ;

Strategy	N_{total}	N_{red}	N_{LRP}
WRA_C	58.8	34.1	1.4
WRA_{MAX}	152.8	42.5	3.0
WRA_{NF}	1052.6	56.2	18.7
WRA_R	2610.4	58.8	44.4

b) F_4 ;

Strategy	N_{total}	N_{red}	N_{LRP}
WRA_C	162.0	50.9	2.4
WRA_{MAX}	342.2	58.8	4.5
WRA_{NF}	2307.6	75.4	30.6
WRA_R	15939.6	78.8	202.0

c) F_5 .

Table 7: Results of experiments with sets of primitive elements in free groups F_3, F_4 and F_5 . Counts are averaged over all inputs.

word. The performance of heuristic algorithms tested on the sets of randomly generated primitive elements shows robust behavior and does not deteriorate when the length of the input words increases.

One of the interesting contributions of this paper is the empirically discovered properties of non-minimal elements of free groups formulated in Conjectures 2.1 and 2.2. These conjectures suggest that the length of a "generic" non-minimal elements in a free group can be reduced by a Nielsen automorphism. Moreover, the feature vectors of the weights of the Whitehead's Graphs of non-minimal elements are divided into "compact" regions in the corresponding vector space. Each such region is related to a particular Nielsen automorphism, that reduces the length of all elements in the region. We believe this is one of those few cases when a meaningful rigorous, but not intuitively clear conjecture, in group theory was obtained by using experimental simulations and statistical analysis of the problem.

It remains to be seen why the algorithm WRA_C is able to find minimal elements using a smaller number of length reductions on average. We are going to address this issue in the subsequent paper.

Strategy	F_3	F_4	F_5
WRA_C	-0.008	-0.001	-0.006
WRA_{MAX}	-0.024	-0.023	-0.038
WRA_{NF}	-0.009	-0.022	-0.022
WRA_R	-0.038	-0.014	-0.035

Table 8: Correlation coefficients between words length and values of N_{LRP} . Negative coefficients indicate that N_{LRP} does not increase when length increases.

References

- [1] R.O. Duda, P.E. Hart, and D.G. Stork, *Pattern classification*, 2nd ed., Wiley-Interscience, 2000.
- [2] K. Fukunaga, *Introduction to statistical pattern recognition*, Academic Press Inc., 1990.
- [3] R.M. Haralick, A.D. Miasnikov, and A.G. Myasnikov, *Pattern recognition approaches to solving combinatorial problems in free groups*, Contemporary Mathematics, v. 349, 2004, p. 197-213.
- [4] R. Lyndon and P. Schupp, *Combinatorial group theory*, Series of Modern Studies in Math. 89. Springer-Verlag, 1977.
- [5] A.D. Miasnikov and A.G. Myasnikov, *Whitehead method and genetic algorithms*, Contemporary Mathematics, Contemporary Mathematics, v. 349, 2004, p. 89-114.
- [6] S. Theodoridis and K. Koutroumbas, *Pattern Recognition*, Academic Press, 1999.
- [7] J. H. C. Whitehead, *On equivalent sets of elements in a free group*, Annals of Mathematics **37** (1936), no. 4, p. 782–800.