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Research Paper

Musical Key Detection Using a Triple Composite Signature of Fifths

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This article introduces a novel algorithm for key detection in musical compositions represented in symbolic form, such as MIDI. The method is based on the analysis of a triple composite signature of fifths (TCSF), which is formed by combining the signatures of fifths obtained individually for the beginning, the end, and the entirety of the analyzed piece. The key is determined by the sign of the angle between the characteristic vector of the TCSF and the major/minor mode axis derived from that signature. To evaluate the algorithm's effectiveness, experiments were conducted using Chopin's Preludes, Op. 28, pieces from the Saarland Music Data: MIDI-Audio Piano Music dataset, as well as pieces from the Schubert Winterreise Dataset. As a reference method, a correlation-based algorithm implementing various tonal profiles was used. The proposed algorithm achieved the highest accuracy for Chopin's Preludes and the Schubert Winterreise Dataset (91.67 % in both cases), while for the Saarland Music Data, its accuracy was lower than that of the correlation-based approaches (72.34 %). The main advantages of the presented algorithm are low computational complexity, stable decision-making when extending the analytical window, as well as incorporation of expert analysis aspects, particularly by focusing on the beginning and end of the composition.

Keywords: key detection, tonality, music information retrieval, music classification.

1. Introduction

The dynamic development of machine learning and artificial intelligence techniques in recent years has contributed to significant advances in computational music analysis, encompassing an increasingly broad range of applications – from acoustic signal processing to advanced structural and semantic analysis of musical pieces (WEIß *et al.*, 2019). Of particular importance in this context is the field of music information retrieval (MIR) and automatic genre classification, which form the foundation of many contemporary applications, such as intelligent recommendation systems, music search engines, and tools supporting artistic creation (KOSTRZEWA *et al.*, 2022; ROSNER, KOSTEK, 2018; SCHEDL *et al.*, 2014; STURM, 2013).

In music genre classification methods, sets of acoustic and musical features are commonly employed – such as spectral centroids, Mel-frequency cepstral coefficients (MFCCs), rhythm, and tempo – which enable effective differentiation of individual compositions and musical styles. These features are utilized not only for genre identification, but also for affective analyses, namely, in determining emotions expressed or evoked by music (CHAPIN *et al.*, 2020; GREKOW, 2018; JUSLIN, SLOBODA, 2010; ROIG *et al.*, 2014; YANG *et al.*, 2023).

A very important and widely studied issue in MIR is the harmonic analysis and evaluation of musical compositions, encompassing automatic chord recognition, local key identification, and the identification of harmonic structures. Research in this area is of key importance for both music genre classification and emotional analysis, as well as the formal segmentation of compositions (Cho, 2013; Harte *et al.*, 2006; Jiang *et al.*, 2024; Mauch, 2010; McFee *et al.*, 2018; Pauwels *et al.*, 2019). Precise determination of harmonic sequences allows for the extraction of characteristic tonal patterns and chord progressions, which form the foundation of many applications such as automatic accompaniment generators, recommendation systems, and tools supporting composition and style analysis (Pauwels *et al.*, 2019). Thanks to the development of machine learning methods, particularly sequential models and deep neural networks, it has become possible to precisely model increasingly complex harmonic dependencies in musical compositions (Bittner *et al.*, 2017; Briot *et al.*, 2020).

Research in the field of affective computing emphasizes the significance of tonality and harmonic structure as key elements in the emotional perception of a musical work. Therefore, in all the aforementioned applications, the precise algorithmic determination of the musical key is of particular importance, and above all, its tonal mode (major/minor), which constitutes one of the most significant indicators affecting the classification of music (Duan *et al.*, 2008). The integration of tonal analysis with modern deep learning methods represents one of the most intensively developing research directions in the field of MIR.

The literature presents many ways of modeling tonality. The most commonly encountered are 2D and 3D models (Chew, 2000; 2008; Longuet-Higgins, 1962a), although more complex, multidimensional models of tonality can also be found (Harte *et al.*, 2006; Bernardes *et al.*, 2016). The origins of 2D tonality representations date back to the work of Leonhard Euler, who proposed a harmonic network called the Tonnetz, depicting the relationships between the pitches of various chords (Euler, 1739). Similar intervallic dependencies were subsequently used in Longuet-Higgins (1962a; 1962b) maps and in various types of spiral spatial models (Chew, 2000; 2008; Shepard, 1982). Recently, approaches to tonal analysis have increasingly relied on artificial intelligence and machine learning algorithms (Dawson, 2018; Deng, Kwok, 2017; Korzeniowski, Widmer, 2017; Zhou, Lerch, 2015). Artificial intelligence methods, in combination with various tonality models, are used, for instance, in automated music composition systems (Huang *et al.*, 2016; Ji, Yang, 2024; Sabathé *et al.*, 2017; Wu *et al.*, 2023).

A very important element used in tonal analysis is tonal profiles, as they allow for the identification of the key of musical pieces (Albrecht, Shanahan, 2013; Herremans, Chew, 2019; Kania, Kania, 2019; Krumhansl, 1990; Temperley, Marvin, 2008). Although many different tonal profiles have been proposed in (Dawson, 2018; Albrecht, Shanahan, 2013; Krumhansl, 1990; Temperley, Marvin, 2008; Aarden, 2003; Bellmann, 2006), it remains unclear whether the problem of determining the key in musical pieces has been solved. Errors in key recognition often result in identifying the relative key or parallel key instead of the ground-truth one, leading to the misclassification of the tonal mode of the analyzed piece (Duan *et al.*, 2008; Łukaszewicz, Kania, 2025a). It is worth noting that alternative methods have also been developed that utilize the tonal relationships expressed in the structure of the circle of fifths (Kania, Kania, 2019; Kania *et al.*, 2024). These models became the starting point for research on the signature of fifths (Łukaszewicz, Kania, 2022; 2025a; 2025b; Kania *et al.*, 2021b).

Work on applying the signature of fifths to detect key signatures (Kania *et al.*, 2021b) and keys (Kania, Kania, 2019; Kania *et al.*, 2024), along with research on the temporal variability of the signature tracking via the trajectory of fifths (Łukaszewicz, Kania, 2025c; Kania *et al.*, 2021a; Kania, Kania, 2022) motivated the development of more refined methods. Kania *et al.* (2024) proposed a simple method of determining the key based on an analysis of the signature of fifths, which measures the deviation of the main directed axis of the signature relative to the major/minor mode axis. The obtained results became the basis for developing a very effective algorithm to classify the tonal mode, presented in a subsequent work (Łukaszewicz, Kania, 2025a). The effectiveness of this approach stems from a multi-criteria assessment of the tonal mode, consisting not only of analysis of the entire piece, but also its beginning and end. This inspired us to seek methods for improving the previously developed key determination method (Kania *et al.*, 2024) by analyzing the directions of characteristic vectors of the signatures of fifths, computed for different segments of an analyzed piece.

The purpose of this article is to present an algorithm for determining the key of a musical composition using a triple composite signature of fifths (TCSF), which is formed by combining the signatures of fifths obtained individually from the beginning, the end, and the entirety of the analyzed piece. The final classification decision is determined by the sign of the angle between the characteristic vector of the TCSF and the major/minor mode axis derived from that signature.

2. Theoretical background

A musical composition constitutes an organized sequence of pitches in which it is typically possible to distinguish a melodic line and an accompaniment layer. The analysis of successive temporal intervals of a composition allows for the determination of changing chord configurations. Frequently, these chords contain notes separated by an octave or its multiples. The choice of the time interval for analysis can be linked to the metric foundation of the examined composition, which also influences the process of constructing the signatures of fifths (Kania, Kania, 2019; Kania *et al.*, 2024).

Let us consider the first quarter-note window of Prelude No. 2 in C minor (BWV 847) by J.S. Bach from the collection Das Wohltemperierte Klavier, Book I, which is shown in Fig. 1. The window contains eight notes: c0, f0, 2 x g0, d1, 2 x e♭1, and c2. Disregarding octave distinctions, the multiplicities of individual pitch classes, after normalization with respect to the maximum multiplicity (which equals 2), are, respectively: $\left|\overrightarrow{C}\right| = \left|\overrightarrow{E\flat}\right| = \left|\overrightarrow{G}\right| = 1$, and $\left|\overrightarrow{D}\right| = \left|\overrightarrow{F}\right| = 0.5$. Assuming a unit radius for the circle of fifths, the normalized multiplicities correspond to the lengths of the vectors forming the signature of fifths presented in Fig. 2.

Fig. 1. Opening fragment of Prelude No. 2 in C minor by J.S. Bach from the collection Das Wohltemperierte Klavier, Book I (BWV 847).

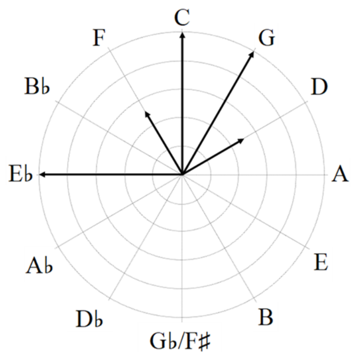

Fig. 2. Signature of fifths corresponding to the first quarter-note window of Prelude No. 2 in C minor by J.S. Bach from the collection Das Wohltemperierte Klavier, Book I (BWV 847), as shown in Fig. 1.

For the signature of fifths, it is possible to determine several characteristic elements that allow for the recognition of the key of the composition (Kania *et al.*, 2024). They include: the main directed axis of the signature of fifths (MDASF) (highlighted in red) – which is the axis for which the difference between the sum of the magnitudes of vectors on the right side and the sum of the magnitudes of vectors on the left side reaches its maximum value, perpendicular to it, the major/minor mode axis (shown in green), and the characteristic vector of the signature of fifths (shown in blue), which is the sum of the vectors forming the signature of fifths (Kania *et al.*, 2024). These elements, corresponding to the signature presented in Fig. 2, are illustrated in Fig. 3. Since only the direction of the characteristic vector of the signature of fifths is important in the key determination algorithm, its

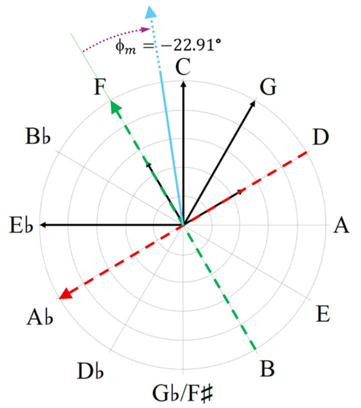

Fig. 3. Signature of fifths and its associated elements: the MDASF (red color), the major/minor mode axis (green color), and the characteristic vector of the signature of fifths (blue color).

length has been shortened, which is symbolically marked with a dashed line. From the perspective of determining the tonal mode, the angle between the characteristic vector of the signature of fifths and the major/minor mode axis is important, i.e., ϕ_m. Detailed information about the method of creating the aforementioned axes and the characteristic vector of the signature of fifths can be found in (Kania *et al.*, 2024).

Each position on the circle of fifths can be associated not only with major keys but also with their corresponding relative minor keys. The direction of the MDASF enables the identification of a pair of relative keys (Kania, Kania, 2019). They are positioned 30° clockwise relative to the keys indicated by the MDASF (Kania, Kania, 2019; Kania *et al.*, 2024). Determining the tonal mode boils down to the selection of one of those keys. For example, for the signature presented in Fig. 3, the pair of relative keys is E♭ major and C minor. The selection of one of the two relative keys can be reduced to determining the value of the angle ϕ_m shown in Fig. 4 (the angle between the characteristic vector of the signature of fifths and the major/minor mode axis) (Kania *et al.*, 2024). In the case considered here, its value is −22.91°, which due to the negative sign indicates a minor key, namely C minor (Kania *et al.*, 2024). It can be seen, therefore, that by analyzing the first quarter-note window of the piece, it was possible to correctly determine the key of the composition.

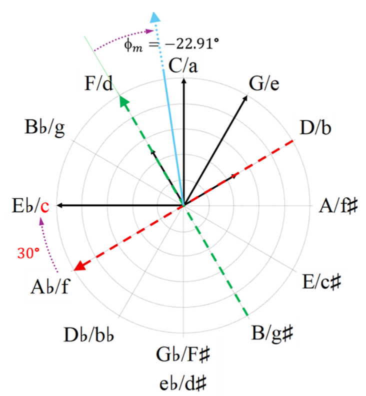

Fig. 4. Illustration of the elements used for key determination based on the signature of fifths (description in the text).

It should be noted that both the coefficients enabling the selection of the direction of the main directed axis and the value of the angle ϕ_m indicate the level of association of the analyzed fragment of the composition with a particular key. Knowing the orientation of the MDASF makes it possible to determine the pair of relative keys. The value of the angle ϕ_m, on the other hand, reflects the 'strength' of the association between the analyzed sample and a particular tonal mode.

Figure 5 illustrates several signatures of fifths corresponding to simple chords. In the first case (Fig. 5a), the signature corresponding to the C major chord is shown. The distribution of vectors in the signature clearly

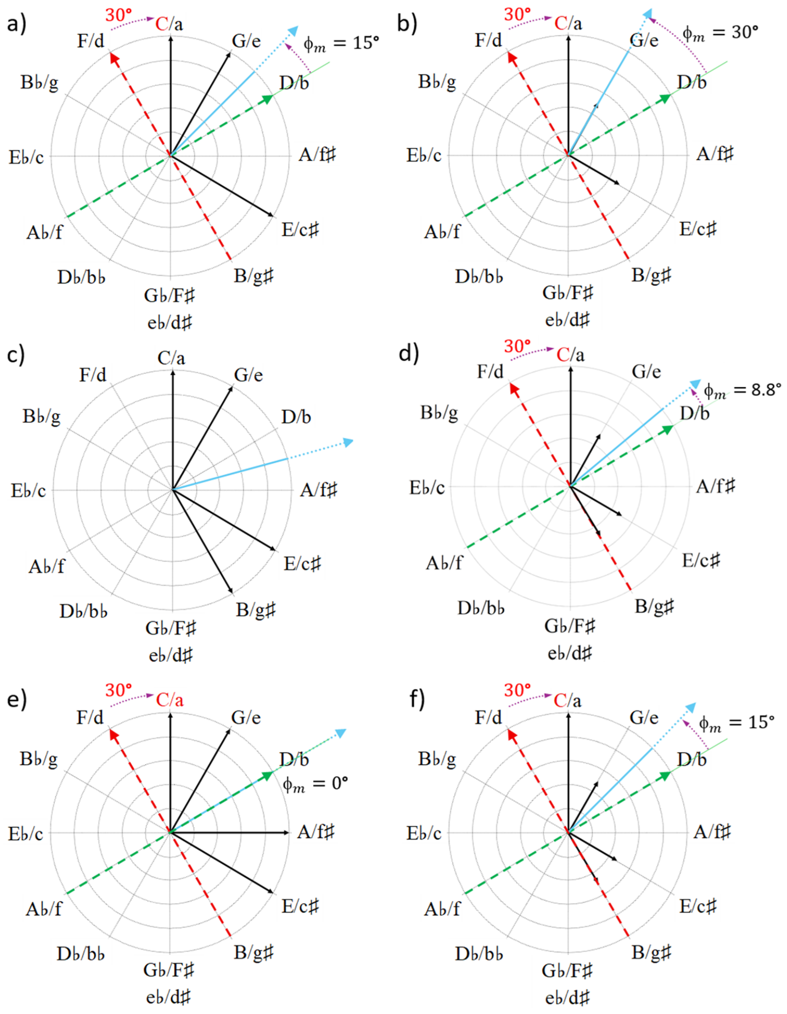

FIG. 5. Example signatures of fifths: a) C major chord, b) C major chord with doubled C note, c) C major seventh chord, d) C major seventh chord with doubled C note, e) C major sixth chord, f) C major sixth chord with doubled C note (description in the text).

indicates the MDASF as B→F. Algebraically, the MDASF is the one for which the difference between the sum of vector lengths on the right side of the axis and the sum of vector lengths on its left side is the greatest (KANIA, KANIA, 2019). In the considered case, its value, represented as the coefficient [B→F], equals 3. The next largest value (i.e., 2) was obtained for the axes: E♭ →B and G♭/F♯ →C. The direction of the MDAFS thus indicates the relative keys C major and A minor. The positive value of the angle ϕ_m, i.e., 15°, indicates the major key, namely C major. In Fig. 5b, the signature corresponding to the C major chord with a doubled tonic is shown. In this case, there is also no doubt regarding the determination of the main directed axis, which is the axis B→F. The larger value of angle ϕ_m, i.e., 30°, more clearly emphasizes the major character of the chord. The situation is different in the case of the C major chord with an added major seventh (C major seventh chord), whose signature is illustrated in Fig. 5c. In this case, there are two directed axes with a maximum value of the coefficient: [B→F] = [G♭/F♯ →C] = 3; hence, for such a sample, the tonality cannot be determined. This is not surprising, since the C major seventh chord contains two triads: C–E–G and E–G–B, of which the first has a clearly major character (C major) and the second a minor character (E minor). Additionally, they belong to two neighboring pairs of relative keys (C major / A minor; G major / E minor). Doubling the note C (Fig. 5d) shifts the balance toward the main axis B→F, indicating the relative keys C major and A minor, and in light of the positive value of the angle $\phi_m = 8.8°$, the major key is chosen, i.e., C major. The situation is different in the case of the C major chord with added sixth (C6), whose signature of fifths is presented in Fig. 5e. As before, it contains two triads: C–E–G and A–C–E, of which the first is major and the second is minor. In this case, the main directed axis is B→F, since these chords are associated with the same pair of relative keys (C major /A minor). The value of the angle $\phi_m = 0°$ does not, however, allow for determining the tonal mode, and therefore the key cannot be unambiguously determined based on the given sample. Doubling the tonic note (for example, C), shown in Fig. 5f, again allows for determining the key as C major.

3. Musical key detection algorithm based on a TCSF

The examples presented in Fig. 6 illustrate various scenarios that can be encountered when attempting to determine the key of a composition based on its selected fragment. Very often, similar ambiguities are observed when analyzing entire compositions. There are compositions that begin in one key and end in another, or while being clearly anchored in a minor key, end with a major chord, and vice versa. It is therefore clear that there is a need to draw conclusions based on several fragments of the analyzed piece. It is worth emphasizing that the method of determining the key using the signature of fifths is quite cautious in making a decision. This distinguishes it from methods utilizing tonal profiles, which tend to frequently change the indicated tonality when the analytical window expands (Kania *et al.*, 2022; 2024). Despite this caution, it would be worthwhile, while maintaining the simplicity of the previously developed algorithms (Kania, Kania, 2019; Kania *et al.*, 2024), to enrich it with information that can further improve the effectiveness of determining the key of a composition.

The results of numerous experiments conducted, including those presented in a previous work (Łukaszewicz, Kania, 2025a), clearly indicate that the best results are obtained when determining the key based on an entire composition. Sometimes the decision made for the entire composition is controversial; hence, it is worthwhile to additionally take into account the results of key detection for the beginning and end of the analyzed piece.

It is reasonable to propose a methodology in which the signature of fifths corresponding to a given piece of music would emphasize the influence of the beginning and ending fragments of the composition, since beginnings and endings of compositions are typically clearly anchored in their tonality.

Through extensive multifaceted work, a form of the signature of fifths was developed that contains the most important information from the perspective of correctly determining the key while maintaining the simplicity of the previously developed algorithms (Kania, Kania, 2019; Kania *et al.*, 2024).

The proposed form of the signature is the TCSF. It consists of three signatures of fifths, which correspond to the entire composition, its beginning, and its end. It is created by summing corresponding components of vectors comprising individual signatures of fifths, followed by normalization relative to the length of the longest vector.

The proposed algorithm for key determination based on the TCSF can be divided into the following general steps:

1. Determination of the signatures of fifths for the beginning and end of the composition (we search for the smallest number of initial/final notes for which it is possible to determine the direction of the MDASF).
2. Determination of the signature of fifths for the entire composition.
3. Determination of the TCSF by summing the corresponding component vectors of individual signatures obtained in steps 1 and 2.
4. Determination of the main directed axis of the TCSF, and identification of the pair of relative keys, as in (Kania, Kania, 2019; Kania *et al.*, 2021b; 2022; 2024).
5. Finding the major/minor mode axis of the analyzed composition, as in (Kania, Kania, 2019; Kania *et al.*, 2021b; 2022; 2024).
6. Determination of the value of the angle ϕ_m between the characteristic vector of the TCSF and the major/minor mode axis.
7. Selection of the tonal mode and one of the relative keys according to the rule:
   - major key when $\phi_m > 0°$,
   - minor key when $\phi_m < 0°$,
   - no decision when $\phi_m = 0°$.

A detailed algorithm is presented in Fig. 6.

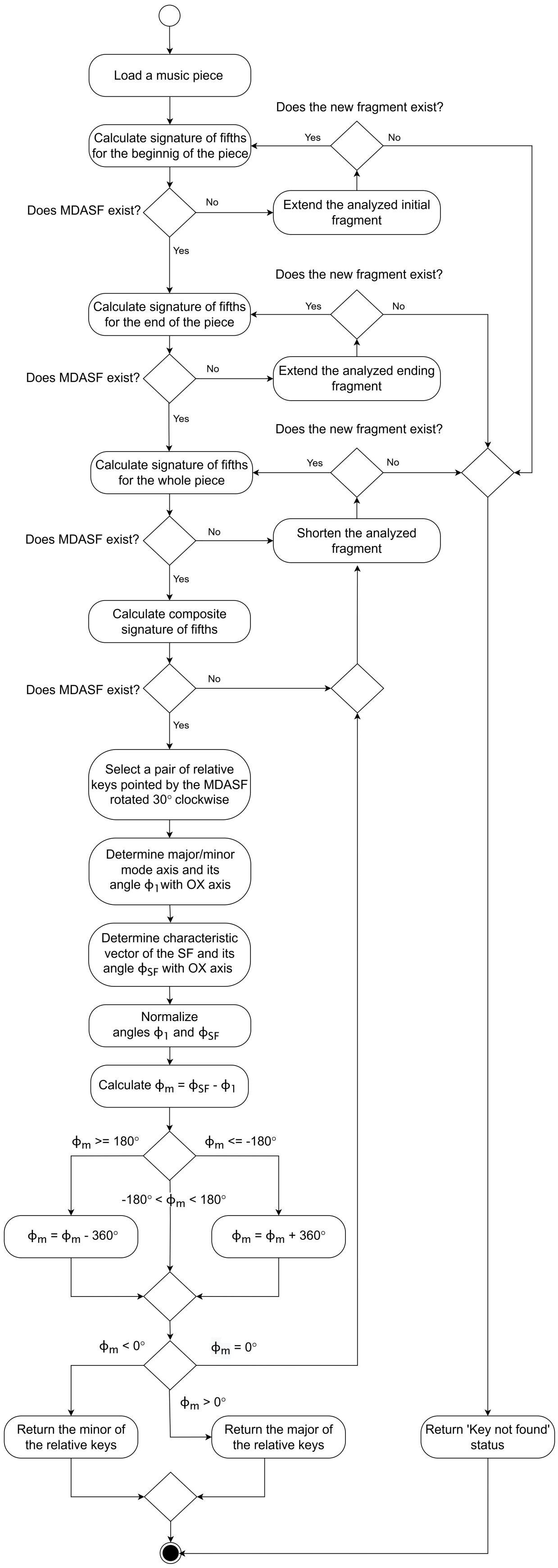

Fig. 6. Diagram presenting the algorithm for determining the key using the TCSF approach.

4. Experiments and discussion

To confirm the effectiveness of recognizing the key using the proposed algorithm, experiments were conducted on classical music compositions from the cycle of 24 Preludes op. 28 by F. Chopin, a collection of piano pieces contained in the Saarland Music Data: MIDI-Audio Piano Music dataset (Müller *et al.*, 2024), and the Winterreise collection, consisting of 24 songs by F. Schubert (Weiß *et al.*, 2020). All of the considered compositions were represented in symbolic form (MIDI files).

The set of Chopin's Preludes, Op. 28 contains compositions in all 24 possible keys, starting from those without key signatures (C major, A minor), then with one sharp (G major, E minor), with two sharps (D major, B minor), and so on, following the arrangement of keys on the circle of fifths. The Saarland Music Data collection contains 50 MIDI files of piano pieces by Bach, Beethoven, Haydn, Mozart, Chopin, Liszt, Bartók, Rachmaninoff, Scriabin, and Ravel. The analysis excluded Béla Bartók's piano sonata Sz. 80 (Müller *et al.*, 2024), as this composition uses the piano in a percussive manner, making it unsuitable for the comparison of key determination algorithms. In the collection of Schubert's Winterreise songs, one can find compositions written in diverse keys, featuring atypical modulations and numerous changes of local key, which make determining the global key of individual songs a non-trivial task. The results of the experiments conducted for the proposed algorithm (TCSF) and correlational approaches utilizing various tonal profiles (KK, T, AE, BB, AS) are presented in Table 1. The values in this table represent the accuracy of key recognition, expressed as the percentage of correctly detected keys in a given set of pieces.

Table 1. Comparison of key detection accuracies across different algorithms.

Algorithm	Chopin's Preludes, Op. 28 [%]	Saarland Music Data: MIDI-Audio Piano Music dataset [%]	Schubert Winterreise dataset [%]
TCSF	91.67	72.34	91.67
KK	79.17	74.47	75
T	83.33	91.49	79.17
AE	87.5	82.98	79.17
BB	87.5	89.36	83.33
AS	75	82.98	75

TCSF – the proposed algorithm using the triple composite signature of fifths approach; KK, T, AE, BB, AS – correlational algorithm implementing Krumhansl-Kessler (Krumhansl, 1990), Temperley (Temperley, 2008), Aarden-Essen (Aarden, 2003), Bellman-Budge (Bellmann, 2006), and Albrecht–Shanahan (Albrecht, Shanahan, 2013) key profiles, respectively.

The results of the conducted experiments showed that the proposed method (TCSF) achieved the highest key recognition accuracy, exceeding 90 %, for the set of Chopin's preludes and Schubert's songs. However, for the compositions contained in the Saarland dataset, significantly lower effectiveness was observed, only 72 %. In this case, the best results (91.49 %) were obtained using correlational method implementing Temperley profiles.

For the set of Chopin's Preludes, Op. 28, the proposed method incorrectly identified the key in two cases: Prelude No. 2 and Prelude No. 18. In the case of Prelude No. 2, the incorrect key identification arises from the specific structure of the composition, where the tonic chord appears only at the very end. Incorrect key determination for this prelude was also observed with the correlational method for all of tonal profiles considered.

An in-depth analysis of the partial results, with particular attention to cases of incorrect key determination, revealed many interesting nuances. In most cases, the classification result was unambiguous, although there were situations in which the detected key was not uniform across the beginning, end, and entirety of a composition. An example is Prelude No. 15, commonly known as the Raindrop Prelude, for which the correct key, i.e., D♭ major, was detected at the beginning and end, but the analysis of the entire composition indicated an incorrect key, i.e., G♯ minor. Analysis of the composition's structure shows that this occurs because the middle section of the piece is composed in C♯ minor. The detected key of G♯ minor likely results from the continuous presence of the note A♭/G♯, associated with the raindrop motif, which is written as A♭ in the first and final parts and as G♯ in the middle section.

An interesting case is Prelude No. 18, which is composed in F minor. However, the piece begins with the note A, which lies outside the F minor scale. This atypical opening causes key determination algorithms to misclassify the key, especially when relying on the initial segment of the composition. The structure of the signature of fifths at the beginning significantly influences the direction of the main axis in the composite signature, resulting in an incorrect outcome for the TCSF method. An in-depth analysis of partial results revealed that increasing the resolution of the analysis to eighth-note windows reduces the impact of the misleading signature of fifths at the beginning, yielding a correct final result. This demonstrates that proper adjustment of the analysis resolution can have a beneficial effect on the effectiveness of key recognition.

When comparing the accuracies of the considered methods for Chopin's Preludes, it is evident that the TCSF algorithm achieves significantly better results than approaches based on tonal profiles. For Prelude No. 2, the correlational method failed to identify the correct key across all profiles used. In the case of Prelude No. 21, only the proposed method correctly determined the key. This outcome is primarily due to the unique approach of the TCSF algorithm, which relies on the signature of fifths and employs 'cautious inference,' without a tendency to change earlier decisions when the analytical window is expanded. This behavior is discussed in detail in (Kania *et al.*, 2024).

In the case of compositions belonging to the Saarland dataset, the effectiveness of key recognition using the proposed method was significantly lower compared to the effectiveness observed for Chopin's preludes. In most cases of incorrect decisions, a key relative to the correct key was indicated (38.46 %). In 23.08 % of cases of incorrect detection, the parallel key was indicated, and in 30.77 %, a key a fifth apart from the correct key. Thus, the method of determining the tonal mode had the greatest impact on the reduction in detection accuracy. This observation is consistent with earlier experiments discussed in (Łukaszewicz, Kania, 2025b). Although it is possible to achieve better results in determining the tonal mode, using the method presented in a related study (Łukaszewicz, Kania, 2025a), it would require the creation and analysis of both the signature and trajectory of fifths (Kania *et al.*, 2021a), increasing the complexity of the algorithm.

In the case of Schubert's compositions, the proposed algorithm consistently outperformed approaches implementing tonal profiles. Only two pieces yielded incorrect results, specifically pieces No. 8 and No. 22. For these compositions, neither the proposed method nor the correlational approaches identified the correct key. These two pieces were composed in G minor, with significant portions in G major, resulting in a distinctly blurred key histogram, further intensified by frequent use of F♯, the third of the major dominant. Additionally, piece No. 8 ends with a G major chord, which unambiguously leads nearly all detection approaches considered (except the one using KK profiles) to identify G major as the key. A detailed analysis of partial results for signatures of fifths generated using the proposed algorithm indicates that, for many pieces, signatures of fifths indicate different keys for the beginning, end, or entirety of a piece. This is not surprising, given the frequent harmonic modulations and changes in local tonalities in Schubert's songs. In 11 pieces, non-uniform directions of the main directed axes in partial signatures of fifths were observed. However, this did not lead to an incorrect determination of the main directed axis of the TCSF, ensuring the correct key determination. For the correlational methods based on different tonal profiles, this variability of local keys, which occurs frequently in the analyzed Schubert's pieces, led to incorrect determination of the global key.

5. Conclusions

The article presented an original method for determining the key of a musical composition using the TCSF. The novelty of the proposed method lies in the way the signature is constructed, which is deeply rooted in the theoretical aspects of music. The concept of creating the TCSF was inspired by the results of experimental research presented in (Kania, Kania, 2019; 2022; Kania *et al.*, 2024; Łukaszewicz, Kania, 2025b).

The main goal of this article was to propose an effective method for determining the key of musical pieces, characterized by the simplicity of algorithms based on the signature of fifths and their inherent stability in the decision-making process as the analytical window expands, and incorporating expert analysis aspects – specifically, paying special attention to the beginning and end of the analyzed composition. The proposed algorithm using the

TCSF effectively fulfilled this goal. The experiments demonstrated the competitiveness of the proposed approach compared to key recognition based on tonal profiles.

An in-depth analysis of the obtained results indicated that the weakest point of the proposed method is the determination of the major/minor tonal mode. This is not surprising, as a similar conclusion emerged from the comparison of key identification algorithms presented in (Łukaszewicz, Kania, 2025c). It may be presumed that better results could be achieved by supplementing the key detection algorithm based on the TCSF with elements of statistical analysis, involving correlation of the signature of fifths obtained for the analyzed sample with tonal profiles, in order to select one of the relative keys indicated by the main directed axis of the signature. The disadvantage of such an approach, however, would be increased computational complexity. One could also use an even more effective method of determining the tonal mode, presented in related research (Łukaszewicz, Kania, 2025a), based on the analysis of the points forming the trajectory of fifths. It may be worthwhile to go even further and, disregarding the TCSF approach, attempt to determine the key of a musical composition based on the distribution of points forming the trajectory of fifths. This approach could be relatively simple and potentially more effective than existing methods.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' contributions

Both authors conceptualized the study, wrote the original draft, performed the analysis and contributed to data interpretation, reviewed and approved the final manuscript.

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