# Providing Meaningful Alignments for Periodic Signs

Alex DillhoffHimanshu PahwaChris ConlyUniversity of Texas at ArlingtonUniversity of Texas at ArlingtonUniversity of Texas at ArlingtonArlington, TX USAArlington, TX USAArlington, TX USAalex.dillhoff@mavs.uta.edupahwa.himanshu@gmail.com chris.conly@uta.edu

Vassilis Athitsos University of Texas at Arlington Arlington, TX USA athitsos@uta.edu

# ABSTRACT

In sign languages, a periodic sign is one that contains repeated movements. Dynamic Time Warping (DTW) is often used in sign language recognition to generate a frame alignment between two input signs that provides a measure of their similarity. Alignments provided by DTW may not be meaningful when the input contains periodic signs, especially when the number of periods differs between inputs. Additionally, the number of periods may change between individual signers and signs. Little work has been done to address the problem of recognizing periodic signs in the context of DTW. This work evaluates two DTW-based approaches. The first uses a newly defined periodic warping path. The second uses manual annotations to truncate periodic input to contain no more than two periods. These two methods are compared against a standard implementation of DTW. Recognition accuracy and quality of alignment are analyzed. The results motivate a need for further research in periodic sign language recognition.

## **CCS** Concepts

•Computing methodologies  $\rightarrow$  Activity recognition and understanding; *Matching*;

## Keywords

sign language recognition; DTW; periodic sequences

# 1. INTRODUCTION

Sign Language Recognition (SLR) is the task of recognizing the sign or signs in a given video sequence. The input sequence is typically a video of a user performing a sign. This work focuses on isolated sign language recognition, in which the input is assumed to be a single sign. An application of this would be an ASL-to-English dictionary system such as the one described in [18].

PETRA '17, June 21 - 23, 2017, Island of Rhodes, Greece

© 2017 Copyright held by the owner/author(s). Publication rights licensed to ACM. ISBN 978-1-4503-5227-7/17/06...\$15.00

DOI: http://dx.doi.org/10.1445/3056540.3056544



Figure 1: Alignment of two similar synthetic examples with differing amounts of periodicity. The input sign (top) has an additional period. The red lines are the points of the resulting warping path.

Many of the signs in American Sign Language consist of a single motion and do not include repeated movements. However, there are a significant number of signs that are periodic in nature. A periodic sign includes at least one repeated movement. The inclusion of an additional movement can change the meaning of a sign from its verb form to the related noun. In many cases, a single movement indicates the verb, whereas an additional repeated movement results in the noun. Examples of this include CHAIR/SIT, AIR-PLANE/FLY, and NEWSPAPER/PRINT [16]. There are also certain signs that add repeated movements to indicate the switch from singular to plural [16]. In some cases, the end of a sign movement can be repeated to provide emphasis. Additionally, the number of periods contained in a sign can vary among signers due to personal signing preference. Figure 3 shows an example of a signer repeating the original motion three additional times. In these cases, the repeated movements do not change the meaning of the sign.

Due to fiscal and time constraints, large vocabulary sign language datasets often contain few examples per sign and are thus not well suited for probabilistic or parameterized methods, which require larger amounts of training data.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.



Figure 2: Meaningful alignment of two similar synthetic examples with differing amounts of periodicity. The input sign (top) has an additional period. This warping path is able to revisit the start of the periodic motion (index 10).

Previous work has focused on the use of DTW [8] for measuring the similarity between two signs. It has shown promising performance for isolated sign language recognition, using as few as one training example per sign class [18].

In DTW, the measure of similarity is based directly on the cost of the frame alignment. When comparing two signs this way, the resulting alignments are only meaningful when the inputs contain the same number of periods. Even with frame length normalization, two inputs that represent the same sign could produce a high alignment cost if they differ in the number of repeated movements.

Figure 1 shows an alignment resulting from two similar synthetic examples with the input example having one additional period. The blue lines are the 1D time signals. The red lines between the two signals indicate the mapping between individual data points as defined by the warping path. Note that the input (top) subsequence (indices 4 to 12) is aligned to a single point (index 5) in the ground truth (bottom) sample. For sign language recognition, this alignment would indicate that the two signs are technically dissimilar even if they are semantically the same. Intuitively, an alignment that matches each period in the input to a similar motion in the ground truth is desired. Figure 2 shows an example of such an alignment.

Two methods based on DTW are evaluated for periodic sign language recognition. The first approach uses a newly defined periodic warping path which allows DTW to produce meaningful alignments between periodic sequences with different numbers of periods. The second approach truncates the input sign so that the redundant periodic motion is not evaluated. Both of these approaches assume that the start of the periodic sequences of a training sign is known in advance. Truncated DTW additionally requires that the start of the periodic sequence of the test sign is known. They can provide more meaningful alignments in cases of periodic inputs. These changes do not adversely affect the runtime.

The recognition accuracy and quality of alignments of the new methods are evaluated using real sign language data. The results show a small improvement in recognition accuracy over standard DTW, and motivate a need for further research of periodic sign language recognition and automatic periodicity detection methods.

# 2. RELATED WORK

Many methods have been applied to the task of Sign Language Recognition. Probabilistic graphical methods such as Hidden Markov Models (HMM) [6, 13, 15, 17] and, by extension, Conditional Random Fields (CRF) [19, 7] have been the most popular. Most of these approaches use an HMM in a Bakis or left-right structure. These structures do not allow transitions to previous states and thus do not explicitly model periodicity.

Machine Learning methods have also been applied. Fang and Gao use a Recurrent Neural Network (RNN) as a segment detector for the task of continuous SLR [4]. Ong et al. use Sequential Patterns (SP) which provide spatio-temporal feature selection in an efficient tree-based classifier [3]. The drawback to using statistical or machine learning methods is their dependence on larger datasets.

The recent popularity of Deep Learning has motivated work in SLR. In [11], Pigou et al. employ a Convolutional Neural Network (CNN) as a feature extractor. The feature vectors output by the CNN are used as input for a neural network based classifier. Koller et al. embed the discriminative power of a CNN into an HMM framework [6]. In this work, the CNN is used to model the emission probability of an HMM.

DTW is an exemplar-based approach that is useful in situations where there is not enough data to train a model. It has been successfully applied in SLR as both a classifier [14, 18] and as a distance measure for extracting the most similar segment between multiple sign sentences [9]. The work presented in this paper evaluates the effect of periodicity in a DTW-based SLR system. We refer the reader to a survey by Cooper et al. for more information on SLR [2].

Previous works have evaluated periodicity. He et al. use HMMs for the task of periodic activity recognition [5]. The structure includes a transition from the last state of the HMM to the beginning. Ruiz et al. show that RNNs can replicate a time varying periodic signal [12]. The work presented in this paper is motivated by that of an earlier study of periodic SLR [10]. A search of the relevant literature produced no other studies of periodicity in the context of sign language recognition.

# 3. METHODS

The aim of this work is to evaluate the recognition of periodic signs using DTW as well as provide a way of improving that performance. In this section, we describe the methods used to evaluate periodic sign data. In section 3.1, the standard definition of a warping path is stated as is used by DTW. Standard DTW is used as the baseline method in our experiments. Section 3.2 defines a periodic warping path which can be used by DTW in order to provide higher quality alignments when comparing signs with different periodicity. In section 3.3, we utilize manual annotations of periodic signs to remove excess periodic movements before applying standard DTW.



(a) The first signer repeats the periodic motion 4 times.



(c) 2D plot of dominant hand movement along x-axis over time for the first signer.



(b) The second signer repeats the periodic motion only 2 times.



(d) 2D plot of dominant hand movement along x-axis over time for the second signer.

Figure 3: Two different signers performing the sign 'calculus'. The number of additional periods varies between the signers. The horizontal location in the plot is relative to the signer's face. The period (blue) and recovery (magenta) arrows represent the motion of the dominant hand along the horizontal axis.

#### 3.1 Dynamic Time Warping

The speed at which a sign is performed can vary between users. DTW produces a warping path which serves as an alignment between the inputs in the time dimension. The cost of aligning two inputs using DTW provides a reliable similarity measure which is useful for classification tasks.

Following the description and notation from [8], given two sign inputs  $X = (x_1, x_2, \ldots, x_N)$  and  $Y = (y_1, y_2, \ldots, y_M)$ , DTW computes a warping path  $W = (w_1, \ldots, w_L)$  of length L where  $w_l = (n_l, m_l)$  refers to the mapping from frame  $X_{n_l}$ to frame  $Y_{m_l}$ . In other words, W provides an alignment between X and Y. The warping path must satisfy the following three constraints: boundary, monotonicity, and step size. The boundary constraint ensures that the first and last frames of X are aligned to the first and last frames of Y. The step size and monotonicity constraints restrict the warping path from skipping frames or jumping backwards in time.

**boundary:** 
$$w_1 = (1, 1)$$
 and  $w_L = (N, M)$   
**monotonicity:**  $n_1 \le n_2 \le \dots \le n_L$  and  
 $m_1 \le m_2 \le \dots \le m_L$   
**step size:**  $w_{l+1} - w_l \in \{(1, 0), (0, 1), (1, 1)\}$   
for  $l \in [1: L - 1]$ .

In sign language recognition, the alignment cost provided by DTW is used for classifying a sign. The cost C(W, X, Y)of a warping path is defined as the sum of the local costs corresponding to the alignment of X and Y:

$$C(W, X, Y) = \sum_{l=1}^{L} c(X_{n_l}, Y_{m_l})$$
(1)

The local cost  $c(X_{n_l}, Y_{m_l})$  can be defined as the Euclidean distance between the feature vectors describing each frame  $X_{n_l}$  and  $Y_{m_l}$ . DTW calculates the overall lowest cost pro-

vided by all possible warping paths:

$$DTW(X,Y) = \min_{W} C(W,X,Y)$$
(2)

The cost of the alignment produced by DTW(X, Y) is then evaluated for all signs  $Y \in \mathbb{Y}$  in the training set. The sign recognized by the system is the label of the sign Y corresponding to the lowest cost returned by DTW(X, Y).

## 3.2 Periodic Warping Path

The standard definition of a warping path provides poor alignments when comparing two similar signs with differing periodicity. As a result, the higher cost of alignment may lead to misclassifications in the sign language recognition system. If the warping path was allowed to revisit periodic movements, DTW could better align data points in the test sign with those that are semantically similar in the training sign.

Following [10], we loosely define a periodic sign by its recovery and period movements. The period movement is defined as the motion required by the signer to gesture the sign. The recovery movement is the motion of returning from the end of the period movement back to the beginning of it. Figure 3 shows two signers performing the sign 'calculus'. The period (blue) and recovery (magenta) motions along the horizontal axis are overlaid onto the image.

In this work, we define a periodic warping path that allows DTW to revisit the start of a periodic movement. Let r be the frame of the start of the recovery motion of a sign. The periodic warping path  $W = (w_1, \ldots, w_L)$  satisfies the following constraints:

**boundary:** 
$$w_1 = (1, 1)$$
 and  $w_L = (N, M)$   
**monotonicity:**  $n_1 \le n_2 \le \dots \le n_L$   
**step size:**  $w_{l+1} - w_l \in \{(1, 0), (0, 1), (1, 1), (0, r - m_l)\}$   
for  $l \in [1: L - 1], m_l > r.$ 

Note that the step size constraint is the only real change between a standard and periodic warping path. The change in the monotonicity constraint is implied by the step size constraint. In practice, DTW can now map multiple frames of the test sign X to that of the recovery start frame in the training sign Y. No other changes need to be made for DTW to provide an alignment using the periodic warping path.

Using the recovery frame r, a periodic warping path can jump back to the beginning of a periodic motion at any point  $m_l > r$ . An example of this is shown in Figure 4. There is no restriction on the number of times DTW can map back to r.

The looser constraints of a periodic warping path may not always lead to a correct result. Using this new definition allows DTW to generate warping paths that were not possible under the standard definition. However, this can lead to misclassifications as well. The periodic warping paths are not a perfect solution to the problem. The periodic subsequences are not uniform. Noise from signing, image capture, and other factors can cause these periodic sequences to vary with respect to a sign. An example of this is shown in Figure 3.

#### **3.3 DTW with Truncated Input**

The final method evaluates the efficacy of standard DTW using truncated inputs. Assuming that the system knows when each period begins in a sign, we truncate each sign



Figure 4: Visualization of the periodic warping path as seen in Figure 2. The input aligns to the end of the ground truth and then jumps back to recovery frame 10.

after the end of the second period. Obviously signs with fewer than 3 periods are not affected by this truncation.

#### 4. EXPERIMENTS

The experiments performed in this work compare the efficacy of the three methods discussed in Section 3. We use the ASLLVD [1] dataset which includes 1,113 distinct sign classes. Each sign class has three examples which are performed by a different user. We focus only on examples that are periodic in nature and consist of a different number of periods between examples. Following [10], we compare signs that are periodic, pure, and non-circular. A periodic and pure sign is one that has a similar trajectory path from one occurrence to the next. A non-circular sign is one that has no circular motions. Between the two subsets used, there are 207 signs that are periodic, pure, and non-circular with a differing number of periods. We use these 207 examples to build the test set.

The manual periodic annotations are provided by earlier work on periodic sign language recognition [10]. We define signs with excess periodic movements as those with more than two periods.

#### 4.1 Evaluation Protocol

The performance of each method is evaluated based on the measures of accuracy described in [18]. Given a query sign X, the measure of performance is the rank R(X) that the method assigns to the correct result for X. Given an integer k, we use a Boolean measure of success S(X,k), that is true iff  $R(X) \leq k$ . The success rate S(k) over a test set of queries is the average success rate S(X, k) over the test set.

## 4.2 Features and Normalization

Following the description given in [18], we extract location and orientation features from each frame of a sign video. The features are derived from the locations of the hands. For these experiments, we use manual annotations provided by [10] to minimize the amount of input noise.

Let X be a sign video of length N.  $X_n$  denotes the *n*-th frame of that video, where  $n \in [1 : N]$ . Each frame of the





Figure 5: The resulting alignment using sign 'beer' as input from (a) DTW, (b) DTW with a periodic warping path, and (c) DTW with truncated inputs.

video provides the following features:

- $L_d(X_n)$  and  $L_{nd}(X_n)$ : The (x, y) centroid corresponding respectively to the dominant hand and non-dominant hand of the signer at frame n.
- $L_{\delta}(X_n)$ : The relative position of the dominant hand with respect to the non-dominant hand at frame *n*.  $L_{\delta}(X_n) = L_d(X_n) - L_{nd}(X_n).$
- $O_d(X_n)$  and  $O_{nd}(X_n)$ : The unit vectors representing the direction of motion from  $L_d(X_{n-1})$  to  $L_d(X_{n+1})$ and from  $L_{nd}(X_{n-1})$  to  $L_{nd}(X_{n+1})$ .
- O<sub>δ</sub>(X<sub>n</sub>): The unit vector representing the direction of motion from L<sub>δ</sub>(X<sub>n-1</sub>) to L<sub>δ</sub>(X<sub>n+1</sub>).

We do not use hand appearance features as described in [18].

For one-handed signs,  $L_{nd}, L_{\delta}, O_{nd}$ , and  $O_{\delta}$  are not calculated. Instead, these features are set to 0 for each frame of the input. All signs are resampled using linear interpolation to have a length of 20 frames for these experiments. The hand locations are normalized with respect to the diagonal of the face bounding box. This normalization is necessary due to the variation in the size of the person signing and their distance from the camera.

Each feature differs in their discriminative capabilities. The range of values is also different between each one. For these reasons, a weighted local cost function is used within DTW. In our implementation, the weighting is done during feature processing. Given the features defined above, the local cost function used is as follows:

$$c(X_{n_{l}}, Y_{m_{l}}) = f_{1} \| L_{d}(X_{n_{l}}) - L_{d}(Y_{m_{l}}) \| + f_{2} \| L_{nd}(X_{n_{l}}) - L_{nd}(Y_{m_{l}}) \| + f_{3} \| L_{\delta}(X_{n_{l}}) - L_{\delta}(Y_{m_{l}}) \| + f_{4} \| O_{d}(X_{n_{l}}) - O_{d}(Y_{m_{l}}) \| + f_{5} \| O_{nd}(X_{n_{l}}) - O_{nd}(Y_{m_{l}}) \| + f_{6} \| O_{\delta}(X_{n_{l}}) - O_{\delta}(Y_{m_{l}}) \|.$$

$$(3)$$

In our experiments, the weights  $f_j$  are optimized using cross-validation on the training set.

#### 4.3 Alignment Visualization

Besides comparing the overall recognition accuracy of these methods, it is important to look at the quality of the alignment provided in each case. By looking at the resulting alignment between two sign inputs with a differing number of periods, we can easily observe how standard DTW is not well suited for periodic signs. Figure 5 shows the alignments provided by each of the described methods. In the figure, the test sample is shown on the top while the training sign is on the bottom. The red lines linking the two examples indicate the alignment provided by DTW. Some of the alignments were removed from the figures for clarity.

In Figure 5b, the green and magenta lines are those that are mapped as a result of the periodic warping path. Note, for example, that point 10 in the input (top) example aligns back to point 8 in the ground truth (bottom) example. This example shows how the periodic warping path allows for a meaningful alignment. The period in the input sign from frame 10 to frame 14 matches the shape in the ground truth from frame 8 to frame 20. Likewise, the magenta alignment



Figure 6: Comparison of DTW with a standard warping path, periodic warping path, and truncated inputs. The results are cross-validated between the TB and LB datasets. The x-axis corresponds to values of K(s).

from input frames 15 to 20 matches the shape of the ground truth from frame 8 to 20. The black vertical line at frame 8 indicates the recovery start frame r.

## 5. RESULTS

The results of the accuracy-based experiment described in section 4 are reported here. We compare standard DTW, DTW with periodic warping paths, and DTW with truncated inputs.

Figure 6 shows a plot of the top-k accuracy of the three DTW-based methods. The final accuracies are averaged between the result of using test samples from TB and training from LB and vice versa. The percentage of queries for which the correct sign is in the top 10 results is 55% for standard DTW, 57% for DTW with periodic alignments, and 64% using DTW with truncated inputs.

Using periodic warping paths shows a small improvement over standard DTW in our experiments. Individual comparisons exemplify the ability of periodic warping paths to provide a lower cost alignment. The alignments provided by this approach match the periodic subsequences in a meaningful way.

The downside to this approach is the ability to provide additional warping paths that were not previously possible under the standard definition. A practical result of this would be a lower cost alignment for signs that are semantically different. An example of this is shown in Figure 7.

The results show a stronger case for using truncated inputs. In both experiments, the overall results were better using DTW with truncated inputs than DTW with periodic warping paths. The first benefit to using truncated inputs is that the standard definition of a warping path can be used. These tightened constraints prevent erroneous alignments as described before. The main benefit of using truncated inputs is that the redundant periods are no longer considered as part of the alignment. The periodic movements signed are typically not rigid and can vary between periods of the same sign.



Figure 7: Two semantically different signs are matched using a periodic warping path. The input sign is 'aunt' and the ground truth sign is 'history'. The red and green lines represent the alignment. The green lines are those that are mapped due to the periodic warping path.

## 6. CONCLUSION

We have evaluated and compared three approaches based on DTW to handling periodic sign data. The first used a standard definition of a warping path. The second utilized a newly defined periodic warping path. The final used truncated inputs based on periodic annotations. For each method, we analyzed two desirable properties: recognition accuracy and the quality of the resulting alignments.

The results of these experiments show a clear improvement in recognition accuracy when the system can properly handle periodic inputs. Using periodic warping paths produced more meaningful alignments which led to a marginal increase in recognition accuracy in our tests. However, the relaxed constraints can lead to warping paths that were not previously possible under the standard definition. This could lead to new misclassifications in a sign language recognition system. For example, two signs that are semantically different could be matched incorrectly. Using truncated inputs with standard DTW produced the greatest accuracy improvement in these experiments.

#### 7. FUTURE WORK

In both the case of periodic warping paths and truncated inputs, the start of the recovery frames is provided by manual annotation. For periodic warping paths, the start of the recovery frames only needs to be provided for the training examples. If we use truncated inputs, the start of the recovery frames also should be known for the test signs. Providing such manual annotations for large datasets is not always feasible and motivates the need for an automatic method. Futhermore, requiring such information to be provided for test signs makes the user interface more cumbersome. Future work will look into detecting the subsequences of a sign to detect recovery periods in an automatic way. The output of these detected recovery periods could be used in place of the manual annotations used in this work.

# 8. ACKNOWLEDGMENTS

This work was partially supported by National Science Foundation grants IIS-1055062 and IIS-1565328.

#### 9. **REFERENCES**

- V. Athitsos, C. Neidle, S. Sclaroff, J. Nash, A. Stefan, Q. Yuan, and A. Thangali. The american sign language lexicon video dataset. In 2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops.
- [2] H. Cooper, B. Holt, and R. Bowden. Sign language recognition. In Visual Analysis of Humans, pages 539–562. Springer, 2011.
- [3] H. Cooper, E.-J. Ong, N. Pugeault, and R. Bowden. Sign language recognition using sub-units. *Journal of Machine Learning Research*, 13(Jul):2205–2231, 2012.
- [4] G. Fang and W. Gao. A srn/hmm system for signer-independent continuous sign language recognition. Proceedings - 5th IEEE International Conference on Automatic Face Gesture Recognition, FGR 2002, pages 312–317.
- [5] Q. He and C. Debrunner. Individual recognition from periodic activity using hidden markov models. In *Human Motion, 2000. Proceedings. Workshop on*, pages 47–52. IEEE, 2000.
- [6] O. Koller, O. Zargaran, H. Ney, and R. Bowden. Deep sign: Hybrid cnn-hmm for continuous sign language recognition. In *Proceedings of the British Machine* Vision Conference 2016, 2016.
- [7] W. W. Kong and S. Ranganath. Towards subject independent continuous sign language recognition: A segment and merge approach. *Pattern Recognition*, (3):1294–1308.
- [8] M. Müller. Chapter 4: Dynamic time warping. *Information Retrieval for Music and Motion*, pages 69–84.
- [9] S. Nayak, K. Duncan, S. Sarkar, and B. Loeding. Finding recurrent patterns from continuous sign language sentences for automated extraction of signs. *Journal of Machine Learning Research*, 13(Sep):2589–2615, 2012.
- [10] H. Pahwa. Handling Periodic Signs in American Sign Language Using Synthetic Generation of Periods. PhD thesis, University of Texas at Arlington, 2010.
- [11] L. Pigou, S. Dieleman, P.-J. Kindermans, and B. Schrauwen. Sign language recognition using convolutional neural networks. In Workshop at the European Conference on Computer Vision, pages 572–578. Springer, 2014.
- [12] A. Ruiz, D. H. Owens, and S. Townley. Existence, learning, and replication of periodic motions in recurrent neural networks. *IEEE Transactions on Neural Networks*, 9(4):651–661, 1998.
- [13] T. Starner and A. Pentland. Real-time american sign language recognition from video using hidden markov models. In *Motion-Based Recognition*, pages 227–243. Springer, 1997.
- [14] M. M. Süzgün, H. Özdemir, N. C. Camgöz, A. A. Kındıroğlu, D. Başaran, C. Togay, and L. Akarun. Hospisign: an interactive sign language platform for hearing impaired. *Deniz Bilimleri ve Mühendisliği Dergisi*, 11(3), 2015.

- [15] S. Theodorakis, V. Pitsikalis, and P. Maragos. Dynamic-static unsupervised sequentiality, statistical subunits and lexicon for sign language recognition. *Image and Vision Computing*, 32(8):533–549, 2014.
- [16] C. Valli. The Gallaudet Dictionary of American Sign Language. Gallaudet University Press, 2005.
- [17] U. Von Agris, D. Schneider, J. Zieren, and K.-F. Kraiss. Rapid signer adaptation for isolated sign language recognition. In 2006 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'06), pages 159–159. IEEE, 2006.
- [18] H. Wang, A. Stefan, S. Moradi, V. Athitsos, C. Neidle, and F. Kamangar. A system for large vocabulary sign search. In *European Conference on Computer Vision*, pages 342–353. Springer, 2010.
- [19] S. B. Wang, A. Quattoni, L.-P. Morency, D. Demirdjian, and T. Darrell. Hidden conditional random fields for gesture recognition. *Proceedings of IEEE Computer Vision and Pattern Recognition*, pages 1521–1527.