

# A Dynamic Programming Approach to De Novo Peptide Sequencing via Tandem Mass Spectrometry

Ting Chen <sup>\*†</sup>    Ming-Yang Kao <sup>‡</sup>    Matthew Tepel <sup>\*</sup>    John Rush <sup>\*</sup>  
George M. Church <sup>\*</sup>

## Abstract

The tandem mass spectrometry fragments a large number of molecules of the same peptide sequence into charged prefix and suffix subsequences, and then measures mass/charge ratios of these ions. The *de novo peptide sequencing* problem is to reconstruct the peptide sequence from a given tandem mass spectral data of  $k$  ions. By implicitly transforming the spectral data into an *NC-spectrum graph*  $G = (V, E)$  where  $|V| = 2k + 2$ , we can solve this problem in  $O(|V| + |E|)$  time and  $O(|V|)$  space using dynamic programming. Our approach can be further used to discover a modified amino acid in  $O(|V||E|)$  time and to analyze data with other types of noise in  $O(|V||E|)$  time. Our algorithms have been implemented and tested on actual experimental data.

## 1 Introduction

The determination of the amino acid sequence of a protein is the first step toward solving the structure and the function of this protein. Conventional sequencing methods [1] cleave proteins into peptides and then sequence the peptides individually using Edman degradation or ladder sequencing by mass spectrometry or tandem mass spectrometry [2]. Among such methods, tandem mass spectrometry combined with microcolumn liquid chromatography has been widely used as follows. A large number of molecules of the same but unknown peptide sequence are selected from a liquid chromatographer and a mass analyzer. Then they are fragmented and ionized by collision-induced dissociation. Finally all the resulting ions are measured by the tandem mass spectrometer for mass/charge ratios. In the process of collision-induced dissociation, a peptide bond at a random position is broken, and each molecule is fragmented into two *complementary* ions, typically an N-terminal b-ion and a C-terminal y-ion. For example, if the  $i$ th peptide bond of a peptide sequence of  $n$  amino acids ( $\text{NH}_2\text{CHR}_1\text{CO} - \text{NHCHR}_2\text{CO} - \dots - \text{NHCHR}_n\text{COOH}$ ) is broken, the N-terminal ion corresponds to a charged prefix subsequence ( $\text{NH}_2\text{CHR}_1\text{CO} - \dots - \text{NHCHR}_i\text{CO}^+$ ) and the C-terminal ion corresponds a charged suffix subsequence ( $\text{NH}_2\text{CHR}_{i+1}\text{CO} - \dots - \text{NHCHR}_n\text{COOH} + \text{H}^+$ ). This process fragments a large number of molecules of the same peptide sequence, and therefore the resulting ions contain almost all possible prefix subsequences and suffix subsequences, and display a spectrum in the tandem mass spectrometer. All these prefix (or suffix) subsequences form a

<sup>\*</sup>Department of Genetics, Harvard Medical School, Boston, MA 02115, USA.

<sup>†</sup>Email: tchen@salt2.med.harvard.edu. Supported by the Lipper Foundation.

<sup>‡</sup>Department of Computer Science, Yale University, New Haven, CT 06520, USA; Email: kao@cs.yale.edu. Supported in part by NSF Grant 9531028.

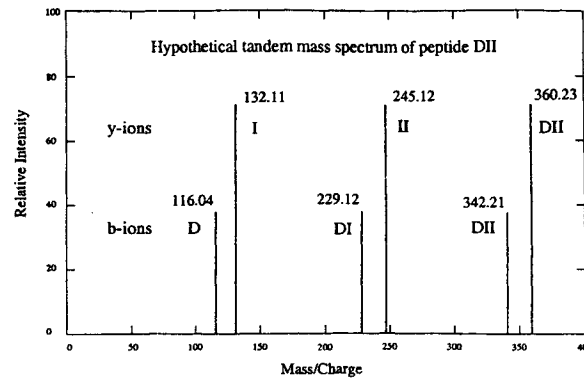


Figure 1: Hypothetical tandem mass spectrum of peptide DII.

sequence ladder where two adjacent sequences differ by one amino acid. In the tandem mass spectrum, each ion appears at the position of its mass because it carries a +1 charge.

Figure 1 shows all the ions of the peptide DII in a hypothetical tandem mass spectrum. The interpretation of a real tandem mass spectrum has to deal with the following two factors: (1) some ions may be lost in the experiments and the corresponding mass peaks disappear in the spectrum; (2) it is unknown whether a mass peak corresponds to a prefix or a suffix subsequence. The *de novo peptide sequencing problem* takes an input of a subset of prefix and suffix masses of a target peptide sequence  $P$  and asks for a peptide sequence  $Q$  such that a subset of its prefixes and suffixes gives the same input masses. Note that as expected,  $Q$  may or may not be the same as  $P$ , depending on the input data and the quality.

In practice, other factors can also affect a tandem mass spectrum. An ion may display two or three different mass peaks because of the distribution of two isotopic carbons,  $C^{12}$  and  $C^{13}$ , in the molecules. An ion may lose a water or an ammonia molecule and displays a different mass peak from its normal one. An amino acid at some unknown location of the peptide sequence is modified and the mass is changed. This modification appears in every molecule of this peptide, and all the ions containing the modified amino acid display different mass peaks from the unmodified ions. Finding the modified amino acid is of great interest to biologists because the modification is usually associated with protein functions.

Several computer programs have been designed to interpret the tandem mass spectral data. A popular approach [3] is to correlate peptide sequences in a protein database with the tandem mass spectrum. Peptide sequences in the database are converted into hypothetical tandem mass spectra, which are matched against the target spectrum using some correlation functions, and the sequences with top scores are reported. This approach gives an accurate identification, but cannot handle the peptides that are not in the database. Also, it does not scale up very well with the length of a protein and the size of a protein database because the number of peptides for a protein grows quadratically with the length of the protein. Pruning techniques have been applied to screen the peptides before matching but at the cost of reduced accuracy.

An alternative approach [4] is *de novo peptide sequencing*. The peptide sequences are extracted from the spectral data before they are validated in the database. First, the spectral data is transformed to a directed acyclic graph, called a *spectrum graph*, where (1) a node corresponds to a mass peak and an edge, labeled by some amino acids, connects two nodes differed by the total mass of the amino acids in the label; (2) a mass peak is transformed

into several nodes in the graph, and each node represents a possible prefix subsequence (ion) for the peak. Then, an algorithm is called to find a longest or highest-scoring path in the graph. The concatenation of edge labels in the path gives one or multiple candidate peptide sequences. However, the well-known algorithms [5] for finding the longest path tend to include multiple nodes associated with the same mass peak. This interprets a mass peak with multiple ions of a peptide sequence, which is rare in practice. This paper provides efficient sequencing algorithms for a general interpretation of the data by restricting a path to contain at most one node for each mass peak.

For this purpose, we introduce the notion of an *NC-spectrum graph*  $G = (V, E)$  for a given tandem mass spectrum, where  $E = 2k + 2$  and  $k$  is the number of mass peaks in the spectrum. In conjunction with this graph, we develop a dynamic programming approach to obtain the following results for previously open problems:

- The de novo peptide sequencing problem can be solved in  $O(|V| + |E|)$  time and  $O(|V|)$  space for clean spectral data, and in  $O(|V||E|)$  time and  $O(|V|^2)$  space for noisy data.
- A modified amino acid can be found in  $O(|V||E|)$  time.

Our paper is organized as follows. Section 2 formally defines the NC-spectrum graph and the peptide sequencing problem. Section 3 describes the dynamic programming algorithms. Section 4 refines the algorithms for the data with a modified amino acid and other types of noise. Section 5 reports the implementation and testing of our algorithms on experimental data. Section ?? mentions further research.

## 2 Spectrum graphs and the peptide sequencing problem

Given the mass  $W$  of a target peptide sequence  $P$ ,  $k$  ions  $I_1, \dots, I_k$  of  $P$ , and the masses  $w_1, \dots, w_k$  of these ions, we create the *NC-spectrum graph*  $G = (V, E)$  as follows.

For each  $I_j$ , it is unknown whether it is an N-terminal ion or a C-terminal ion. If  $I_j$  is a C-terminal ion, it has a complementary N-terminal ion, denoted as  $I_j^c$ , with a mass of  $W - w_j$ . Therefore, we create two complementary nodes  $N_j$  and  $C_j$  to represent  $I_j$  and  $I_j^c$ , one of which must be an N-terminal ion. We also create two auxiliary nodes  $N_0$  and  $C_0$  to represent the zero-length and full-length N-terminal ions of  $P$ . Let  $V = \{N_0, N_1, \dots, N_k, C_0, C_1, \dots, C_k\}$ . Each node  $x \in V$ , is placed at a real line, and its coordinate  $\text{cord}(x)$  is the total mass of its amino acids, i.e.,

$$\text{cord}(x) = \begin{cases} 0 & x = N_0; \\ W - 18 & x = C_0; \\ w_j - 1 & x = N_j \quad \text{for } j = 1, \dots, k; \\ W - w_j & x = C_j \quad \text{for } j = 1, \dots, k. \end{cases}$$

This coordinate scheme is adopted for the following reasons. An N-terminal b-ion has an extra Hydrogen (approximately 1 dalton), so  $\text{cord}(N_j) = w_j - 1$  and  $\text{cord}(C_j) = (W - (w_j - 1)) - 1 = W - w_j$ ; and the full peptide sequence of  $P$  has two extra Hydrogens and one extra Oxygen (approximately 16 daltons), so  $\text{cord}(C_0) = W - 18$ . If  $\text{cord}(N_i) = \text{cord}(C_j)$  for some  $i$  and  $j$ ,  $I_i$  and  $I_j$  are complementary: one of them corresponds to a prefix sequence and another corresponds to the complementary suffix sequence. In the spectrum graph, they are

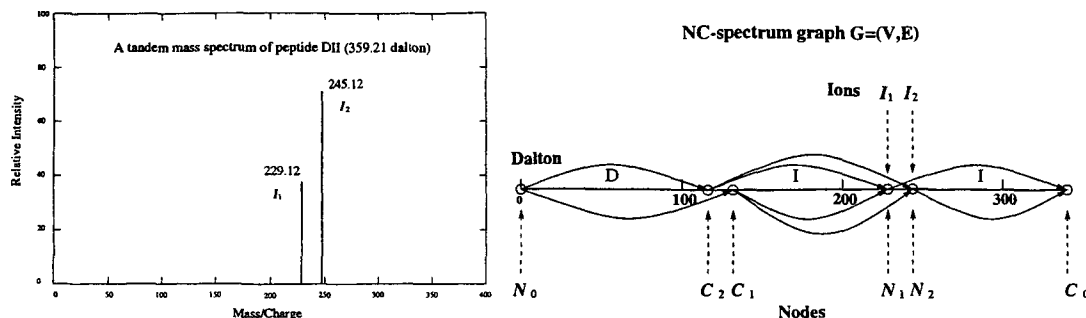


Figure 2: A tandem mass spectrum and its corresponding NC-spectrum graph.

transformed into one pair of complementary nodes. We say that  $N_j$  and  $C_j$  are *derived* from  $I_j$ . For convenience, for  $x$  and  $y \in V$ , if  $\text{cord}(x) < \text{cord}(y)$ , then we say  $x < y$ .

The edges of  $G$  are specified as follows. For  $x$  and  $y \in V$ , there is a directed edge from  $x$  to  $y$ , denoted by  $E(x, y) = 1$ , if the following conditions are satisfied: (1)  $x$  and  $y$  are not derived from the same  $I_j$ ; (2)  $x < y$ ; and (3)  $\text{cord}(y) - \text{cord}(x)$  equals the total mass of some amino acids. Figure 2 shows a tandem mass spectrum and its corresponding NC-spectrum graph.

Since  $G$  is a directed graph along a line and all edges point to the right on the real line, we list the nodes from left to right according to their coordinates as  $x_0, x_1, \dots, x_k, y_k, \dots, y_1, y_0$ .

**Lemma 1** *The peptide sequencing problem is equivalent to the problem which, given  $G = (V, E)$ , asks for a directed path from  $x_0$  to  $y_0$  which contains exactly one of  $x_j$  and  $y_j$  for each  $j > 0$ .*

*Proof.* If the peptide sequence is known, we can identify the nodes of  $G$  corresponding to the prefix subsequences of this peptide. These nodes form a directed path from  $x_0$  to  $y_0$ . Generally the mass of a prefix subsequence does not equal the mass of any suffix subsequence, so the path contains exactly one of  $x_j$  and  $y_j$  for each  $j > 0$ .

A satisfying directed path from  $x_0$  to  $y_0$  contains all observed prefix subsequences. If each edge on the path corresponds to one amino acid, we can visit the edges on the path from left to right, and concatenate these amino acids to form a peptide sequence that display the tandem mass spectrum. If some edge corresponds to multiple amino acids, we obtain more than one peptide sequences.

Even if the mass of a prefix subsequence coincidentally equals the mass of a suffix subsequence, which means the directed path contains both  $x_j$  and  $y_j$ , we can remove either  $x_j$  or  $y_j$  from the path and form a new path corresponding to multiple peptide sequences which contain the real sequence.  $\square$

We call such a directed path a *feasible reconstruction* of  $P$  or a *feasible solution* of  $G$ . To construct  $G$ , we use a mass array  $A$ , which takes an input of mass  $m$ , and returns 1 if  $m$  equals the total mass of some amino acids; and 0 otherwise. Let  $h$  be the maximum mass under construction. Let  $\delta$  be the measurement precision for mass. Then,

**Theorem 2** *Assume that we are given the maximum mass  $h$  and the mass precision  $\delta$ .*

1. *The mass array  $A$  can be constructed in  $O(\frac{h}{\delta})$  time.*
2. *With  $A$ ,  $G$  can be constructed in  $O(k^2)$  time.*

*Proof.* These statements are proved as follows.

Statement 1. Given a mass  $m$ ,  $0 < m \leq h$ ,  $\mathcal{A}[m] = 1$  if and only if  $m$  equals one amino acid mass, or there exists an amino acid mass  $r < m$  such that  $\mathcal{A}[m - r] = 1$ . If  $\mathcal{A}$  is computed in the order from  $\mathcal{A}[0]$  to  $\mathcal{A}[\frac{h}{\delta}]$ , each entry can be determined in constant time since there are only 20 amino acids. The total time is  $O(\frac{h}{\delta})$ .

Statement 2. For any two nodes  $v_i$  and  $v_j$  of  $G$ , we create an edge for  $v_i$  and  $v_j$ ,  $E(v_i, v_j) = 1$ , if and only if  $0 < \text{cord}(v_j) - \text{cord}(v_i) < h$  and  $\mathcal{A}[\text{cord}(v_j) - \text{cord}(v_i)] = 1$ . There are  $O(k^2)$  pairs of nodes. With  $\mathcal{A}$ ,  $G$  can be constructed in  $O(k^2)$  time.  $\square$

In current practice,  $\delta = 0.01$  dalton, and  $h = 400$  daltons, roughly the total mass of four amino acids. The efficiency of our algorithm will allow biologists to consider much larger  $h$  and much smaller  $\delta$ .

### 3 Algorithms for peptide sequencing

#### 3.1 Dynamic programming

We list the nodes of  $G$  from left to right as  $x_0, x_1, \dots, x_k, y_k, \dots, y_1, y_0$ . Let  $M(i, j)$  be a two-dimension table with  $0 \leq i, j \leq k$ . Let  $M(i, j) = 1$  if and only if in  $G$ , there is a path  $L$  from  $x_0$  to  $x_i$  and a path  $R$  from  $y_j$  to  $y_0$ , such that  $L \cup R$  contains exactly one of  $x_p$  and  $y_p$  for every  $p \in [0, i] \cup [0, j]$ . Let  $M(i, j) = 0$  otherwise.

**Algorithm Compute-M( $G$ )**

1. Initialize  $M(0, 0) = 1$  and  $M(i, j) = 0$  for all  $i \neq 0$  or  $j \neq 0$ ;
2. Compute  $M(1, 0)$  and  $M(0, 1)$ ;
3. For  $j = 2$  to  $k$
4.   For  $i = 0$  to  $j - 2$ 
  - (a) if  $M(i, j - 1) = 1$  and  $E(x_i, x_j) = 1$ , then  $M(j, j - 1) = 1$ ;
  - (b) if  $M(i, j - 1) = 1$  and  $E(y_j, y_{j-1}) = 1$ , then  $M(i, j) = 1$ ;
  - (c) if  $M(j - 1, i) = 1$  and  $E(x_{j-1}, x_j) = 1$ , then  $M(j, i) = 1$ ;
  - (d) if  $M(j - 1, i) = 1$  and  $E(y_j, y_i) = 1$ , then  $M(j - 1, j) = 1$ .

**Lemma 3** Given  $G(V, E)$ , Algorithm Compute-M computes the table  $M$  in  $O(|V|^2)$  time.

*Proof.* Let  $L$  and  $R$  be the paths that correspond to  $M(i, j) = 1$ . If  $i < j$ , by definition, after removing node  $y_j$  from  $R$ ,  $L \cup R - \{y_j\}$  contains exactly one of  $x_q$  and  $y_q$  for all  $1 \leq q \leq j - 1$ . If  $(y_j, y_p) \in R$ , then  $M(i, p) = 1$ , and either  $p = j - 1$  or  $i = j - 1$ , which corresponds to Step 4(b) or 4(d) respectively in the algorithm, because either  $x_{j-1}$  or  $y_{j-1}$ , but not both, is in  $L \cup R$ . A similar analysis holds for the cases of Step 4(a) or 4(c). The loop at Step 3 uses previously computed  $M(0, j - 1), \dots, M(j - 1, j - 1)$  and  $M(j - 1, 0), \dots, M(j - 1, j - 1)$  to fill up  $M(0, j), \dots, M(j, j)$  and  $M(j, 0), \dots, M(j, j)$ . Thus the algorithm computes  $M$  correctly. Note that  $|V| = 2k + 2$  and Steps 4(a), 4(b), 4(c), and 4(d) take  $O(1)$  time, and thus the total time is  $O(|V|^2)$ .  $\square$

**Theorem 4** The following statements hold.

1. Given  $G = (V, E)$  and  $M$ , a feasible solution of  $G$  can be found in  $O(|V|)$  time.

2. Given  $G = (V, E)$ , a feasible solution of  $G$  can be found in  $O(|V|^2)$  time and  $O(|V|^2)$  space.
3. Given  $G = (V, E)$ , all feasible solutions of  $G$  can be found in  $O(|V|^2 + n|V|)$  time and  $O(|V|^2 + n|V|)$  space, where  $n$  is the number of solutions.

*Proof.* These statements are proved as follows.

Statement 1. Note that  $|V| = 2k + 2$ . Without loss of generality, assume that a feasible solution  $S$  contain node  $x_k$ . Then there exists some  $j < k$ , such that  $(x_k, y_j)$  is an edge in  $S$  and  $M(k, j) = 1$ . Therefore, we search the non-zero entries in the last row of  $M$  and find a  $j$  that satisfies both  $M(k, j) = 1$  and  $E(x_k, y_j) = 1$ . This takes  $O(|V|)$  time. With  $M(k, j) = 1$ , we backtrack  $M$  to search the next edge of  $S$  as follows. If  $j = k - 1$ , the search starts from  $i = k - 2$  to 0 until both  $E(x_i, x_k) = 1$  and  $M(i, j) = 1$  are satisfied; otherwise  $j < k - 1$ , and then  $E(x_{k-1}, x_k) = 1$  and  $M(k - 1, j) = 1$ . We repeat this process to find every edge of  $S$ . The process visits every node of  $G$  at most once in the order from  $x_k$  to  $x_0$  and from  $y_k$  to  $y_0$ . The total cost is  $O(|V|)$  time.

Statement 2. We compute  $M$  by means of Lemma 3 and find a feasible solution by means of Statement 1. The total cost is  $O(|V|^2)$  time and  $O(|V|^2)$  space.

Statement 3. The proof is similar to that of Statement 1. We can find all the feasible solutions by backtracking  $M$ , and each feasible solution costs  $O(|V|)$  time and  $O(|V|)$  space. Computing  $M$  and finding  $n$  solutions cost  $O(|V|^2 + n|V|)$  time and  $O(|V|^2 + n|V|)$  space in total.  $\square$

### 3.2 An improved algorithm

To improve the time and space complexities in Theorem 4, we encode  $M$  into two linear arrays. Define an edge  $(x_i, y_j)$  with  $0 \leq i, j \leq k$  to be a *cross edge*, and an edge  $(x_i, x_j)$  or  $(y_j, y_i)$  with  $0 \leq i < j \leq k$  to be an *inside edge*. Let  $\text{lce}(z)$  be the length of the longest consecutive inside edges starting from node  $z$ ; i.e.,

$$\begin{cases} \text{lce}(x_i) = j - i & \text{if } E(x_i, x_{i+1}) = \dots = E(x_{j-1}, x_j) = 1 \text{ and } (j = k \text{ or } E(x_j, x_{j+1}) = 0); \\ \text{lce}(y_i) = i - j & \text{if } E(y_i, y_{i-1}) = \dots = E(y_{j+1}, y_j) = 1 \text{ and } (j = 0 \text{ or } E(y_j, y_{j-1}) = 0). \end{cases}$$

Let  $\text{dia}(z)$  be two diagonals in  $M$ , where

$$\begin{cases} \text{dia}(x_j) = M(j, j - 1) & \text{for } 0 < j \leq k; \\ \text{dia}(y_j) = M(j - 1, j) & \text{for } 0 < j \leq k; \\ \text{dia}(x_0) = \text{dia}(y_0) = 1. \end{cases}$$

**Lemma 5** Given  $\text{lce}(\cdot)$  and  $\text{dia}(\cdot)$ , any entry of  $M$  can be computed in  $O(1)$  time.

*Proof.* Without loss of generality, let the  $M(i, j)$  be the entry we want to compute where  $0 \leq i < j \leq k$ . If  $i = j - 1$ ,  $M(i, j) = \text{dia}(y_j)$  as defined; otherwise  $i < j - 1$  and  $M(i, j) = 1$  if and only if  $M(i, i + 1) = 1$  and  $E(y_j, y_{j-1}) = \dots = E(y_{i+2}, y_{i+1}) = 1$ , which is equivalent to  $\text{dia}(y_{i+1}) = 1$  and  $\text{lce}(y_j) \geq j - i - 1$ . Thus both cases can be solved in  $O(1)$  time.  $\square$

**Lemma 6** Given  $G = (V, E)$ ,  $\text{lce}(\cdot)$  and  $\text{dia}(\cdot)$  can be computed in  $O(|V| + |E|)$  time.

*Proof.* We retrieve consecutive edges starting from  $y_k, y_{k-1}, \dots$ , until the first  $y_p$  with  $p \leq k$  and  $E(y_p, y_{p-1}) = 0$ . Then we can fill  $\text{lce}(y_k) = k - p$ ,  $\text{lce}(y_{k-1}) = k - p - 1, \dots$ , and  $\text{lce}(y_p) = 0$  immediately. Next, we start a new retrieving and filling process from  $y_{p-1}$ , and repeat this until  $y_0$  is visited. Eventually we retrieve  $O(k)$  consecutive edges. A similar process can be applied to  $x$ . Using a common graph data structure such as a link list, a consecutive edge can be retrieved in constant time, and thus  $\text{lce}(\cdot)$  can be computed in  $O(|V|)$  time.

By definition,  $\text{dia}(x_j) = M(j, j-1) = 1$  if and only if there exists some  $i$  with  $0 \leq i < j-1$ ,  $M(i, j-1) = 1$ , and  $E(x_i, x_j) = 1$ . If we have computed  $\text{dia}(x_0), \dots, \text{dia}(x_{j-1})$  and  $\text{dia}(y_{j-1}), \dots, \text{dia}(y_0)$ , then  $M(i, j-1)$  can be computed in constant time by means of the proof in Lemma 5. To find the  $x_i$  for  $E(x_i, x_j) = 1$ , we can visit every inside edge that ends at  $x_j$ . Therefore the computation of  $\text{dia}(\cdot)$  visits every inside edge exactly once, and the total time is  $O(|V| + |E|)$ .  $\square$

**Theorem 7** Assume that  $G(V, E)$  is given.

1. A feasible solution of  $G$  can be found in  $O(|V| + |E|)$  time and  $O(|V|)$  space.
2. All feasible solutions of  $G$  can be found in  $O(n|V| + |E|)$  time and  $O(n|V|)$  space, where  $n$  is the number of solutions.

*Proof.* These statements are proved as follows.

Statement 1. By Lemma 6,  $\text{lce}(\cdot)$  and  $\text{dia}(\cdot)$  can be computed in  $O(|V| + |E|)$  time and  $O(|V|)$  space. By Lemma 5, the last row and the last column of  $M$  can be reconstructed from  $\text{lce}$  and  $\text{dia}$  in  $O(|V|)$  time. By Theorem 4 and Lemma 5, a feasible solution of  $G$  can be found in  $O(|E|)$  time. Therefore, finding a feasible solution takes  $O(|V| + |E|)$  time and  $O(|V|)$  space.

Statement 2. The proof is similar to the proof of Statement 3 in Theorem 4. Finding an additional feasible solution takes  $O(|V|)$  time and  $O(|V|)$  space. Thus finding  $n$  solutions takes  $O(n|V| + |E|)$  time and  $O(n|V|)$  space.  $\square$

A feasible solution of  $G$  is a path of  $k+1$  nodes and  $k$  edges, and therefore there must exist an edge between any two nodes on the path by the edge transitive relations. This implies that there are at least  $(k+1)k/2$  or  $O(|V|^2)$  edges in the graph. However, in practice, a threshold is usually set for the maximum length (mass) of an edge, so the number of edges in  $G$  could be much smaller than  $O(|V|^2)$  and may actually equal  $O(|V|)$  sometimes.

## 4 Algorithms for noisy data

### 4.1 Amino acid modification

Amino acid modifications are related to protein functions. For example, some proteins are active when phosphorylated but inactive when dephosphorylated. Although there are a few hundred known modifications, a peptide rarely has two or more modified amino acids. This section discusses how to find the position of a modified amino acid from a tandem mass spectral data. We assume that the modified mass is unknown and is not equal to the total mass of any number of amino acids; otherwise, it is information-theoretically impossible to detect an amino acid modification from tandem mass spectral data.

**Lemma 8** The amino acid modification problem is equivalent to the problem which, given  $G = (V, E)$ , asks for two nodes  $v_i$  and  $v_j$ , such that  $E(v_i, v_j) = 0$  but adding the edge  $(v_i, v_j)$  to  $G$  creates a feasible solution that contains this edge.

*Proof.* Similar to Lemma 1.  $\square$

Let  $G = (V, E)$  be an NC-spectrum graph with nodes from left to right as  $x_0, \dots, x_k, y_k, \dots, y_0$ . Let  $N(i, j)$  be a two-dimension table with  $0 \leq i, j \leq k$ , where  $N(i, j) = 1$  if and only if there is a path from  $x_i$  to  $y_j$  which contains exactly one of  $x_p$  and  $y_p$  for every  $p \in [i, k] \cup [j, k]$ . Let  $N(i, j) = 0$  otherwise.

**Algorithm Compute-N( $G$ )**

1. Initialize  $N(i, j) = 0$  for all  $i$  and  $j$ ;
2. Compute  $N(k, k - 1)$  and  $N(k - 1, k)$ ;
3. For  $j = k - 2$  to  $0$
4.   For  $i = k$  to  $j + 2$ 
  - (a) if  $N(i, j + 1) = 1$  and  $E(x_j, x_i) = 1$ , then  $N(j, j + 1) = 1$ ;
  - (b) if  $N(i, j + 1) = 1$  and  $E(y_{j+1}, y_j) = 1$ , then  $N(i, j) = 1$ ;
  - (c) if  $N(j + 1, i) = 1$  and  $E(x_j, x_{j+1}) = 1$ , then  $N(j, i) = 1$ ;
  - (d) if  $N(j + 1, i) = 1$  and  $E(y_i, y_{j+1}) = 1$ , then  $N(j + 1, j) = 1$ .

**Lemma 9** Given  $G = (V, E)$ , Algorithm Compute-N computes the table  $N$  in  $O(|V|^2)$  time.

*Proof.* Similar to Lemma 3.  $\square$

**Theorem 10** Given  $G = (V, E)$  which contains all prefix and suffix nodes, all possible amino acid modifications can be found in  $O(|V||E|)$  time and  $O(|V|^2)$  space.

*Proof.* Let  $M$  and  $N$  be two tables for  $G$  computed from Lemma 3 and 9. Without loss of generality, let the modification be between two consecutive prefix nodes  $x_i$  and  $x_j$  with  $0 \leq i < j \leq k$  and  $E(x_i, x_j) = 0$ . All the prefix nodes to the right of  $x_j$  have the same mass offset from the normal locations because the corresponding sequences contain the modified amino acid. By adding a new edge  $(x_i, x_j)$  to  $G$ , we create a feasible solution  $S$  that contains this edge. If  $i + 1 < j$ , then  $y_{i+1} \in S$ , and thus  $M(i, i + 1) = 1$  and  $N(j, i + 1) = 1$ . There are  $O(k^2)$  possible combinations of  $i$  and  $j$ , and checking all of them takes  $O(|V|^2)$  time. If  $i + 1 = j$ , then  $S$  must contain an edge  $(y_q, y_p)$  with  $q > j > i > p$ , which skips over  $y_i$  and  $y_j$ .  $S$  can be found if  $E(y_q, y_p) = 1$  and  $M(i, p) = 1$  and  $N(j, q) = 1$ . There are at most  $O(|E|)$  edges, which can be examined in  $O(|E|)$  time. Checking  $O(|V|)$  possible  $i + 1 = j$  costs  $O(|V||E|)$  time. The total complexity is  $O(|V||E|)$  time and  $O(|V|^2)$  space.  $\square$

Note that the condition in Theorem 10 does not require that all ions in the spectrum are observed. If some ions are lost but their complementary ions appear,  $G$  still contains all prefix and suffix nodes of the target sequence. Furthermore, if  $G$  does not contain all prefix and suffix nodes because of many missing ions, we can still use this algorithm to find the modification but the result depends on the quality of the data and the modified mass.

## 4.2 Using scoring functions

In practice, a tandem mass spectral data may contain noise such as mass peaks of other types of ions from the same peptide, mass peaks of ions from other peptides, and mass peaks of unknown ions. A common way to deal with these situations is to use a pre-defined edge scoring function  $s(\cdot)$ . With  $s$ , the score of a path is the sum of the scores of the edges on the path. We re-define the *peptide sequencing problem*, which given an NC-spectrum graph



$G = (V, E)$ , asks for a maximum score path from  $x_0$  to  $y_0$ , such that at most one of  $x_j$  and  $y_j$  for every  $1 \leq j \leq k$  is on the path.

Let  $Q(i, j)$  be a two-dimension table with  $0 \leq i, j \leq k$ .  $Q(i, j) > 0$  if and only if in  $G$ , there is a path  $L$  from  $x_0$  to  $x_i$  and a path  $R$  from  $y_j$  to  $y_0$ , such that at most one of  $x_p$  and  $y_p$  is in  $L \cup R$  for every  $p \in [0, i] \cup [0, j]$ ;  $Q(i, j) = 0$  otherwise. If  $Q(i, j) > 0$ , let  $Q(i, j)$  be the maximum score among all  $L$  and  $R$  pairs.

#### Algorithm Compute-Q( $G$ )

1. Initialize  $Q(0, 0) = 1$  and  $Q(i, j) = 0$  for all  $i \neq 0$  or  $j \neq 0$ ;
2. For  $j = 1$  to  $k$
3.     For  $i = 0$  to  $j - 1$ 
  - (a) For every  $E(y_j, y_p) = 1$  and  $Q(i, p) > 0$ ,  $Q(i, j) = \max\{Q(i, j), Q(i, p) + s(y_j, y_p)\}$ ;
  - (b) For every  $E(x_p, x_j) = 1$  and  $Q(p, i) > 0$ ,  $Q(j, i) = \max\{Q(j, i), Q(p, i) + s(x_p, x_j)\}$ .

**Lemma 11** *Given  $G = (V, E)$ , Algorithm Compute-Q computes the table  $Q$  in  $O(|V||E|)$  time.*

*Proof.* The correctness proof is similar to that for Lemma 3. For every  $j$ , Steps 3(a) and 3(b) visit every edge of  $G$  at most once, so the total time is  $O(|V||E|)$ .  $\square$

**Theorem 12** *Given  $G = (V, E)$ , a feasible solution of  $G$  can be found in  $O(|V||E|)$  time and  $O(|V|^2)$  space.*

*Proof.* Algorithm Compute-Q computes  $Q$  in  $O(|V||E|)$  time and  $O(|V|^2)$  space. For every  $i$  and  $j$ , if  $Q(i, j) > 0$  and  $E(x_i, y_j) = 1$ , we compute the sum  $Q(i, j) + s(x_i, y_j)$ . Let  $Q(p, q) + s(x_p, y_q)$  be the maximum value, and we can backtrack  $Q(p, q)$  to find all the edges of the feasible solution. The total cost is  $O(|V||E|)$  time and  $O(|V|^2)$  space.  $\square$

## 5 Experimental results

We have presented algorithms for reconstructing peptide sequences from a tandem mass spectral data with loss of ions. This section reports experimental studies which focus on cases of b-ions losing a water or ammonia molecule and cases of isotopic varieties for an ion. We treat the rare occurrence such as y-ions losing a water or ammonia molecule, b-ions losing two water or ammonia molecules, and other types of ions, as noise and apply Algorithm Compute-Q to reconstruct peptide sequences.

Isotopic ions come from isotopic carbons of  $C^{12}$  and  $C^{13}$ . An ion usually has a couple of isotopic forms, and the mass difference between two isotopic ions is generally one or two daltons. Their intensities reflect the binomial distribution between  $C^{12}$  and  $C^{13}$ . This distribution can be used for identification. Isotopic ions can be merged to one ion of either the highest intensity or a new mass.

It is very common for a b-ion to lose a water or ammonia molecule. In the construction of an NC-spectrum graph, we add three types of edges whose lengths equal the masses of a water molecule, amino acids minus one water, and amino acids plus one water respectively. In Algorithm Compute-Q, we restrict the net number of waters at each entry to be at most one, since a feasible solution should have a net of zero water. We have implemented this algorithm and tested it on the data generated by the following process:

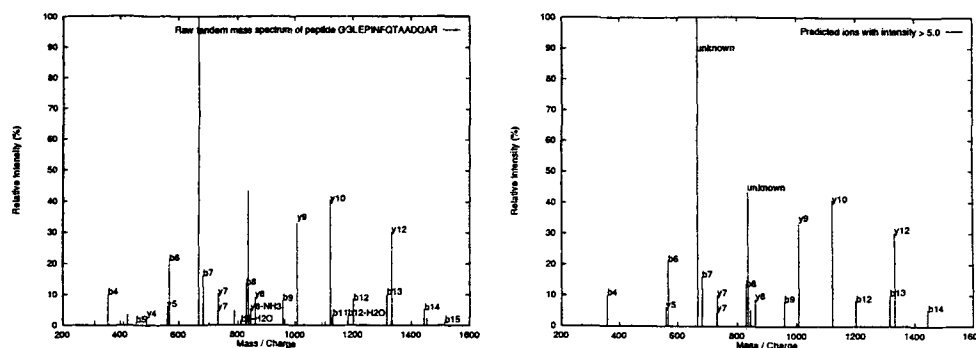


Figure 3: Raw tandem mass spectrum and predicted ions of the Chicken Ovalbumin peptide GGLEPINFQTAADQAR.

The Chicken Ovalbumin proteins were digested with trypsin in 100 mM ammonium bicarbonate buffer pH 8 for 18 hours at 37°C. Then 100  $\mu$ l are injected in acetonitrile into a reverse phase HPLC interfaced with a Finnigan LCQ ESI-MS/MS mass spectrometer. A 1% to 50% acetonitrile 0.1%TFA linear gradient was executed over 60 minutes.

Figure 3 shows one of our prediction results. The ions labeled in the spectrum were identified successfully. We use resolution 1.0 dalton and relative intensity threshold 5.0 in our program. More experimental results will be shown in the full version of this paper.

## 6 Further research

We are working on the cases of multiple peptides.

## References

- [1] Wilkins, M.R. & Williams, K.L. & Appel, R.D. & Hochstrasser, D.F. (1997). *Proteome Research: New Frontiers in Functional Genomics*. (Springer-Verlag).
- [2] McLafferty, F.W. & Fridriksson, E.K. & Horn, D.M. & Lewis, M.A. & Zubarev, R.A. (1999). Biomolecule Mass Spectrometry. *Science*. **284**: 1289-1290.
- [3] Eng, J.K. & McCormack, A.L. & Yates, J.R. (1994). An Approach to Correlate Tandem Mass Spectral Data of Peptides with Amino Acid Sequences in a Protein Database. *Journal of American Society for Mass Spectrometry*. **5**, 976-989.
- [4] Dancik, V. & Addona, T.A. & Clauser, K.R. & Vath, J.E. & Pevzner, P.A. (1999). De Novo Peptide Sequencing via Tandem Mass Spectrometry: A Graph-Theoretical Approach. *Proceedings of the 3rd Annual International Conference on Computational Molecular Biology*.
- [5] Comen, T.H. & Leiserson, C.E. & Rivest, R.L. (1990). *Introduction to Algorithms*. (The MIT Press).