

Statistical Machine Translation adding Rule based Machine Translation

Jin'ichi Murakami
Department of Information and
Knowledge Engineering
Faculty of Engineering
4-101 koyamachou Tottori City
Tottori 680-8552, Japan
murakami@ike.tottori-
u.ac.jp

Masato Tokuhisa
Department of Information and
Knowledge Engineering
Faculty of Engineering
4-101 koyamachou Tottori City
Tottori 680-8552, Japan
tokuhisa@ike.tottori-
u.ac.jp

Satoru Ikehara
Department of Information and
Knowledge Engineering
Faculty of Engineering
4-101 koyamachou Tottori City
Tottori 680-8552, Japan
ikehara@ike.tottori-
u.ac.jp

ABSTRACT

We have developed a two-stage machine translation (MT) system. The first stage is a rule-based machine translation system. The second stage is a normal statistical machine translation system. For Japanese-English machine translation, first, we used a Japanese-English rule-based MT, and we obtained "ENGLISH" sentences from Japanese sentences. Second, we used a standard statistical machine translation. This means that we translated "ENGLISH" to English machine translation. We believe this method has two advantages. One is that there are fewer unknown words. The other is that it produces structured or grammatically correct sentences.

From the results of experiments, we obtained a BLEU score of 0.2565 in the Intrinsic-JE task using our proposed method. In contrast, we obtained a BLEU score of 0.2165 in the Intrinsic-JE task using a standard method (moses). And we obtained a BLEU score of 0.2602 in the Intrinsic-EJ task using our proposed method. In contrast, we obtained a BLEU score of 0.2501 in the Intrinsic-EJ task using a standard method (moses).

This means that our proposed method was effective for the Intrinsic-JE and Intrinsic-EJ task. For the future study, we will try to improve the performance by optimizing parameters.

Categories and Subject Descriptors

I.2.7 [Natural Language Processing]: Machine translation

General Terms

Languages

Keywords

SMT Rule-Based MT Hybrid System

1. INTRODUCTION

Many machine translation systems have been studied for long time and there was three generations of this technology.

The first generation was a rule-based translation method, which was developed over the course of many years. This method had translation rules that were written by hand. Thus, if the input sentence completely matched the rule, the output sentence had the best quality. However, many expressions are used for natural language, this technology had very small coverage. In addition, the main problem are that the cost to write rules was too high and that maintaining the rules was hard.

The second generation was example-based machine translation method. This method finds a similar sentence from corpus and generates a similar output sentence. The problem with this method is calculating the similarity. Many methods like dynamic program (DP) are available. However, they are very heuristic and intuitive and not based on mathematics.

The third generation was a statistical machine translation method and this method is very popular now. This method is based on the statistics, and it seems very reasonable. There are many versions of statistical machine translation models available. An early model of statistical machine translation was based on IBM1 ~ 5[1]. This model is based on individual words, and thus a "null word" model is needed. However, this "null word" model sometimes has very serious problems, especially in decoding. Thus, recent statistical machine translation systems usually use phrase based models. This phrase based statistical machine translation model has translation model and language model. The phrase table is a translation model for phrase-based SMT and consists of Japanese language phrases and corresponding English language phrases and these probabilities. And word N -gram model is used as a language model. By the way, there are two points to evaluate English sentences for Japanese to English machine translation. One is adequacy, and the other is fluency. We believe adequacy is related to translation model $P(English|Japanese)$ and fluency is related to language model $P(English)$.

However some problems arise with phrase-based statistical machine translation. One problem is as follows. Normally, a translation model requires a large parallel corpus. However, if we use a smaller parallel corpus, it results in many unknown words in the output translation. The second problem is that normally, an N -gram model is used as a language model. However, this model consists of local language information and does not have grammatical information.

In Japanese-English translation, the first stage consists of Japanese-English rule-based machine translation. In this stage, we obtained "ENGLISH" sentences from Japanese sentences. We aim to achieve "ENGLISH" sentences that contain few unknown words and that are generally grammatically correct. However, these "ENGLISH"

sentences have low levels of fluency and naturalness because they were obtained using rule-based machine translation. In the second stage, we used a normal statistical machine translation system. This stage involves "ENGLISH" to English machine translation. With this stage, we aim to revise the outputs of the first stage improve the naturalness and fluency.

We used IBM King504 (翻訳の王様 in Japanese) for the first stage. We used general statistical machine translation tools for the second stage, such as "Giza++" [5], "moses" [7], and "training-phrase-model.perl" [10]. And, we could not use all data for restrict of computer memory and computational costs. We used only NTCIR-7 data. It means we used only 1798571 sentences. Also, the score was not optimized, and our method was still very promising. We used these data and these tools and participated in the Intrinsic-JE, Intrinsic-EJ, and Extrinsic-JE. at NTCIR-8.

From the results of experiments, we obtained a BLEU score of 0.2565 in the JE task using our proposed method. In contrast, we obtained a BLEU score of 0.2165 in the Intrinsic-JE task using a standard method (moses). And we obtained a BLEU score of 0.2602 in the Intrinsic-EJ task using our proposed method. In contrast, we obtained a BLEU score of 0.2501 in the Intrinsic-EJ task using a standard method (moses). This means that our proposed method was effective for all task.

As the results, the proposed method was effective for all task. Even though we used only NTCIR-7 database(1798571 sentences), our system had average performance for NTCIR-7 Patent Translation task [14]. For example, our system was the 11th place in 20 system for Intrinsic-JE task and the 19th place in 22 system for Intrinsic-EJ task.

For the future study, we will try to improve the performance by using all NTCIR-8 and NTCIR-7 database and by optimizing parameters. So, we will continue to develop the method and try again in the future.

2. RELATED WORKS

Our system has a two-stage machine translation system. The first stage is a rule-based machine translation system, and the second stage is a normal statistical machine translation system. This idea was based on paper[3],[4],[5]. Similar studies were on paper[12],[13],[15][11]. [12] and [13] was Fresh-English translation and used SYSTRAN. [11] was Chinese-English translation for patent task and used SYSTRAN. [15] was Japanese-English translation for patent task.

3. CONCEPTS OF OUR STATISTICAL MACHINE TRANSLATION SYSTEM

Our statistical machine translation consists of a two-stage translation system. The first stage is rule-based machine translation, and the second stage is statistical machine translation. We describe our system by dividing it into two processes, training and decoding. These processes are assumed to be Japanese-English translation.

3.1 Training

The training process is as follows.

1. Parallel Corpus

We prepare a Japanese-English parallel corpus.

2. Rule-based Machine Translation

We used a Japanese-English rule-based machine translation. Thus, we obtain "ENGLISH" sentences from Japanese sentences. These "ENGLISH" sentences are pairs of English sentences.

3. Make "ENGLISH"-English phrase table

We make an "ENGLISH"-English phrase table using training-phrase-model.perl[10].

4. English *N*-gram model

We make an *N*-gram model from English sentences using SRILM [6].

Fig. 1 shows the flow chart of the training process.

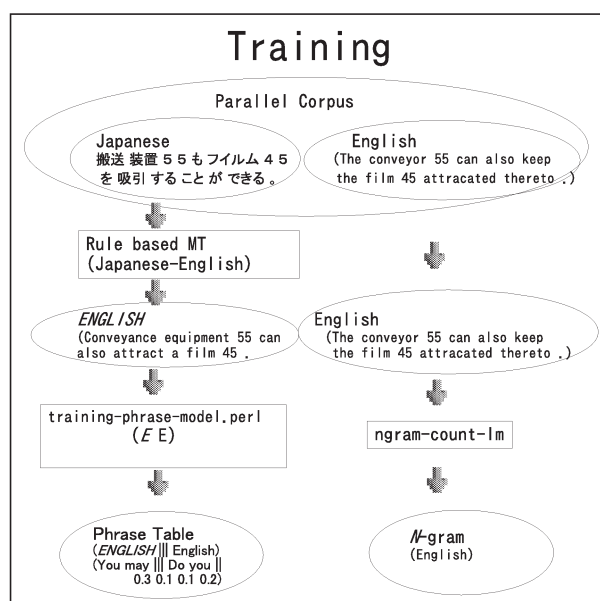


Figure 1: Flowchart of Training

3.2 Decoding

The decoding process is as follows.

1. Test Corpus

We prepare the Japanese test sentences.

2. Rule-based Machine Translation

We used a Japanese-English rule-based machine translation. Thus, we obtain "ENGLISH" test sentences.

3. Statistical Machine Translation System

Using phrase table in Section 3.1, *N*-gram model in Section 3.1, and moses[7], we decode the "ENGLISH" sentences. This involves "ENGLISH"-English translation. In this way, we obtain English sentences.

Fig.2 shows the flow chart of the decoding process.

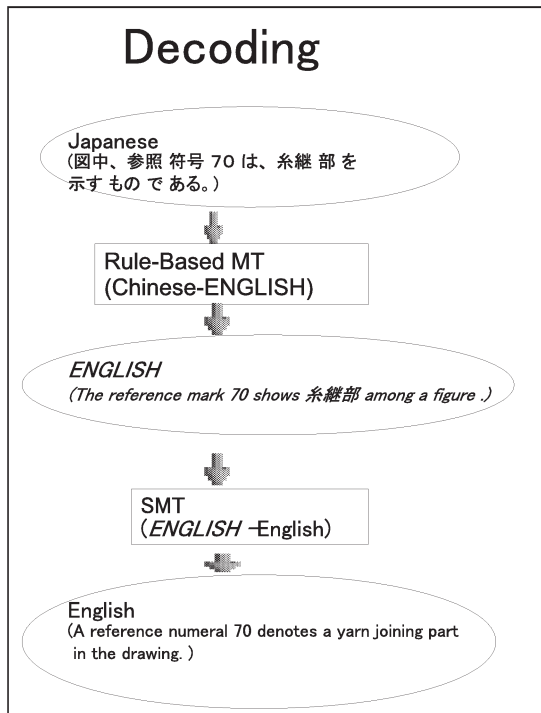


Figure 2: Flowchart of Decoding

4. EXPERIMENTS WITH OUR MACHINE TRANSLATION

4.1 Training Data

We used the English punctuation procedure, which means that we changed "," and "." to " ," and " ." . Also, we did not handle English case forms. Also, we could not use all data for restrict of computer memory and computational costs. We used only NTCIR-7 data. It means we used only 1798571 sentences.

4.2 First Stage

We used IBM King504 (翻訳の王様 in Japanese) for the first stage. For terms of IBM in Table 5 shows examples of the first stage (IBM) output.

4.3 "ENGLISH"- "English" Phrase Tables

For the second stage, we made an ENGLISH-English phrase table. To make this table, we used "train-phrase-model.perl[10]" in "training-release-1.3.tgz". We set parameters to default values.

Table 1 lists examples of phrase tables for the second stage of our MT. This phrase table represents an "ENGLISH" "English" phrase table. As seen in this table, some English phrases are natural, although some of them are unnatural.

4.4 5-gram Language Model

We calculated the 5-gram model using ngram-count in the Stanford Research Institute Language Model (SRILM) toolkit [6], and used "-ukndiscount -interpolate" as the smoothing parameter.

4.5 Decoder

We used "Moses[7]" as a decoder. In Japanese to English translation, the position of the verb is sometimes significantly changed

Table 1: Examples of phrase-tables

Extremely appropriate . It fits very well .	1 0.0037774 1 0.000165701
Extremely appropriate It fits very well	1 0.00394828 1 0.000167943
Extremely attractive . It is very beautiful .	0.00468009 0.5 0.000167226
Extremely attractive . Very beautiful .	1 0.121764 0.5 0.0529012
Extremely attractive It is very beautiful	1 0.00489181 0.5 0.000169488
Extremely attractive Very beautiful	1 0.127273 0.5 0.053617
want to go to eat meal . like to have dinner .	1 4.70488e-06 0.5 0.00340606
want to go to eat meal . want to go to the restaurant .	1 1.02487e-05 0.5 4.7193e-06
want to go to eat meal like to have dinner	0.333333 4.91772e-06 0.5 0.00345215
want to go to eat meal want to go to the restaurant	1 1.07123e-05 0.5 4.78316e-06
want to go to eat like to have	0.0222222 3.18012e-05 1 0.0191019
you eaten ? you tried ?	1 0.0705182 1 0.0519143
you eaten you tried	1 0.0714764 1 0.0524031

from its original position. Thus, we set the "distortion weight (weight-d)" to "0.2" and "distortion-limit" to "-1" for standard statistical machine translation. However, our system has 2 stage machine translation and the output of first stage is "ENGLISH". In this case, the position of word did not move so widely. So, we set the "distortion-limit" to "-6" for second stage statistical machine translation for our system.

Table 2 indicates the other parameters. We did not optimize these parameters nor use a reordering model.

Table 2: Parameters of mooses.ini

ttable-limit	40	0			
weight-d	0.1				
weight-l	1.0				
weight-t	0.5	0.0	0.5	0.1	0.0
weight-w	-1				
distortion-limit	(-1 or 6)				

5. RESULTS OF OUR MACHINE TRANSLATION

Table 3 summarizes the results of our machine translation evaluation for the Intrinsic-JE and Intrinsic-EJ tasks. In this table, "Proposed" indicates our proposed system, "Baseline" indicates the normal statistical machine translation (moses).

Table 3: Results

	task	bleu
Proposed (TORI)	Intrinsic-JE	0.2565
Baseline (moses)	Intrinsic-JE	0.2156
Proposed (TORI)	Intrinsic-EJ	0.2602
Baseline (moses)	Intrinsic-EJ	0.2501

As seen in these results, our method was so effective, as indicated by the BLEU score.

6. DISCUSSION

With our system, we aim to reduce the number of unknown words and ungrammatical sentences. Thus, we analyze the outputs according to these factors.

6.1 Unknown Words

If we compare the outputs of Moses and of our system, we find very few unknown words. Therefore, the proposed method is effective in reducing the number of unknown words.

6.2 Grammatical Correctness

We analyzed the outputs of our MT system. However, there were no native speakers of English to check the inputs and outputs. Therefore, it was impossible to analyze these results for detail and could not determine what was wrong. However, by comparing the output of Moses and the output of our system, we found that our system produced more grammatically correct sentences. Therefore, the BLEU score was so good.

7. CONCLUSION

We have developed a two-stage machine translation system. The first stage is a rule-based machine translation system. The second stage is a statistical machine translation system. Our goal with this system was to obtain fewer unknown words and fewer ungrammatical sentences. The results that we obtained in this experiment were so good.

We did not use all training data nor optimize parameters nor did we use a reordering model. In future experiments, we will try these data and these techniques, which we expect will enable our system to perform better.

8. APPENDIX: EXPERIMENTS WITH ALL TRAINING DATA

We tried to use all training data (2920434 sentence) to improve these results. Also we did not use reordering models or not optimize these parameters using MERT in this experiment.

Table 4 shows the results of these experiments. As can be seen in this table, proposed method was so effective for BLEU score. The proposed BLEU score was the best group of NTCIR-8.

Table 4: Appendix: Results with All data

	task	bleu	nist	meteor
Proposed	Intrinsic-JE	0.2924	7.2904	0.6216
Baseline (moses)	Intrinsic-JE	0.2229	6.1266	0.5842
Proposed	Intrinsic-EJ	0.3276	7.5638	
Baseline (moses)	Intrinsic-EJ	0.3232	7.2663	

9. ACKNOWLEDGEMENTS

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Table 5: Outputs for Intrinsic-JE

107	Input	図 1 1 において、高圧ポンプ吐出量が大き、または、小のとき、スビル弁駆動タイミングの変化量に対し高圧ポンプ吐出量の変化量が小さい。
	Proposed	In FIG . 11 , when high-pressure pump discharge quantity is larger , the amount of change is small with respect to the amount of change in the amount of discharge of the high pressure pump spill valve drive timing .
	Baseline	In FIG . 11 , the high-pressure pump discharge quantity is large or small , or when the spill valve drive timing variations with respect to variation of the high-pressure pump discharge quantity is small .
	IBM	In Fig . 11 , when high-pressure pump 吐出量 is size or smallness , the amount of change of high-pressure pump 吐出量 is small to the amount of change of スビル valve drive timing .
	REFERENCE	In FIG . 11 , when the high-pressure pump discharge quantity is large or small , the change quantity in the high-pressure pump discharge quantity is small with respect to the change quantity in the spill valve drive timing .
108	Input	フィードフォワード量演算部 1 0 0 では、燃料噴射弁から各気筒に供給される燃料量と同量の燃料がフィードフォワード量 $Q F_{inj}$ として設定され、PID 制御部 2 0 0 では目標燃圧 $P F_o$ と燃圧 $P F$ に基づいてフィードバック量 $Q F_{sp1}$ が算出される。
	Proposed	The amount of each cylinder is calculated based on the target fuel pressure $P F_o$ and the fuel pressure $P F$ to the PID control unit 200 , and the feedback amount is set as the feed forward amount from the fuel injection valve in an amount equal the amount of fuel supplied to the fuel feed forward operation section 100 , $Q F_{inj}$ $Q F_{sp1}$.
	Baseline	The amount of fuel $Q F$ is set as a final fuel injection amount $Q F_{inj}$ based on the fuel pressure $P F$ and the target fuel pressure $P F_o$ and the PID control unit 200 as a feedback signal . $2 pl$ is calculated from the fuel injection valve feed forward amount calculating section 100 is supplied to each cylinder of the feed forward amount .
	IBM	In the amount operation part 100 of フィード forwards , the fuel of the amount of fuel supplied to each cylinder from a fuel injection valve and the amount of said is set up as an amount $Q F_{inj}$ of フィード forwards , and the amount $Q F_{sp1}$ of feedbacks is computed based on target 燃圧 $P F_o$ and 燃圧 $P F$ in the PID control part 200 .
	REFERENCE	In the feedforward quantity computing unit 100 , the same quantity of fuel as the quantity of fuel supplied from the fuel injection valve to each cylinder is set as a feedforward quantity $Q F_{inj}$, and in the PID control unit 200 , a feedback quantity $Q f_{sp1}$ is calculated on the basis of the target fuel pressure $P F_o$ and the fuel pressure $P F$.
109	Input	まず、所定の範囲が機関回転速度に基づき変更される場合、しきい値 1 $X P F H$ 、しきい値 2 $X P H L$ は、例えば図 7 のように設定される。
	Proposed	First , as shown in FIG . 7 , when the predetermined range is changed based on the engine rotational speed N , and the threshold value $1 X P F H$ $2 X P H L$ are set .
	Baseline	First , the engine speed is within a predetermined range based on a change in the threshold value 1 is set , for example , as shown in FIG . 2 , the threshold value $H X P F X P H L$.
	IBM	First , as shown in Fig . 7 , when the predetermined range is changed based on organization rotation speed , threshold $1 X P F H$ and threshold $2 X P H L$ are set up .
	REFERENCE	First , when the predetermined range is changed on the basis of the engine rotation speed , the threshold value $1 X P F H$ and the threshold value $2 X P F L$ are set as shown in FIG . 7 , for example .
111	Input	次に図 1 4 の動作説明図を参照しながら、上記のように構成された筒内燃料噴射式内燃機関の燃料圧力制御装置における第二のフィードバック量の挙動について説明する。
	Proposed	Next , the operation of the second feedback quantity of the fuel pressure control apparatus for a direct injection type internal combustion engine combustion chamber , shown in FIG . 1 will now be described with reference to the flow chart of FIG . 14 .
	Baseline	A description will now be given , with reference to FIG . 14 of the direct cylinder fuel injection control device for an internal combustion engine having the above structure will now be described as a second feedback amount of the behavior of the fuel pressure .
	IBM	Next , the action of the second amount of feedbacks in the fuel pressure control device of the charge injection formula internal combustion engine of pipe internal combustion constituted as mentioned above is explained , referring to the diagram of Fig . 14 of operation .
	REFERENCE	Next , the behavior of the second feedback quantity in the fuel pressure control apparatus of the cylinder fuel injection type internal combustion engine configured as described above will be described with reference to FIG . 14 .
112	Input	ここで積分項 $P F F B _ I$ が式 (A) より大きいとき (即ち、 $Y E S$)、ステップ S 4 0 9 で次式により、しきい値 $1 X P F H$ 以上の量を除いた目標吐出量 $Q F_{sp1}$ を算出する。
	Proposed	When the integral term I is larger than the target amount of one or more of threshold values is calculated using the following equation at step S409 . $X P F H s$ $Q F_{sp1}$ except for the discharge amount (i.e . , YES) , $P F F B$ equation (A)
	Baseline	The integral term $I / F _ B$ is larger than the threshold (that is , YES) , the routine proceeds to step 409 , the amount of the target discharge quantity Q is calculated . 1 excluding at least 1 according to the following equation (A) $P F$ type $X P F p l F s$.
	IBM	When integration clause $P F F B _ I$ is larger than a formula (A) (namely , YES) , target 吐出量 $Q F_{sp1}$ except the quantity of 1 or more $X P F H s$ of thresholds is computed by the following formula at Step S409 here .
	REFERENCE	Here , when the integral term $P F F B _ I$ is larger than the expression (A) (i.e . , YES) , the target discharge quantity $Q F_{sp1}$ excluding a quantity equal to or greater than a threshold value $1 X P F H$ is calculated by the following expression in step S409 .

Input means input Japanese sentence. Proposed means the output our proposed method. Baseline means the output of Moses.

IBM means the output of IBM King504 (翻訳の王様). REFERENCE means the correct sentence and handmade.

Table 6: Outputs for Intrinsic-EJ

5	Input	Through the temperature control circuit (CPU) , the operation of the heater is controlled so that the temperature to be detected by each thermistor becomes the target temperature .
	Proposed	それぞれのサーミスタの検出温度が設定温度になるように、ヒータ温度制御回路（CPU）によってその動作が制御される。
	Baseline	これにより、ヒータ温度制御回路（CPU）の動作を制御することにより、夫々のサーミスタの温度が目標温度を検出する。
	IBM	温度コントローラ一周（CPU）を通して、それぞれのサーミスタによって見つけられる温度が目標温度になるように、ヒータの操作は、コントロールされます。
	REFERENCE	温度調節回路（CPU）により、それぞれのサーミスタにおいて検知された温度が目標温度となるようにヒータの動作が制御される。
6	Input	As the abnormal temperature rise observed in this embodiment is up to approximately 190 °C , the high-temperature offset and downtime are not caused .
	Proposed	この実施例では、約190°C、#x+bで観測しているために、停止時間ずれや高温異常な温度上昇が立ち上る。は発生しない。
	Baseline	また、本実施の形態では約190°Cまで昇温された異常停止し、高温オフセットが発生しない。
	IBM	異常な温度増加がこれで体現が上がっていることを観察したので、おおよそ190°Cに、C。高温のオフセットと非稼働時間は、引き起こされません。
	REFERENCE	本例では異常昇温が190°C程度までであったため、高温オフセットやダウンタイムは、発生しない。
8	Input	The fixing roller 51 rotates clockwise as indicated by the arrow .
	Proposed	矢印で示すように、定着ローラ51は時計方向に回転する。
	Baseline	また、定着ローラ51は矢示の時計方向に回転する。
	IBM	矢によって示されるように、固定しているローラ51は、時計回りに回転します。
	REFERENCE	また、定着ローラ51は矢印の時計方向に回転駆動される。
13	Input	FIG . 8 shows the belt , seen from the fixing roller .
	Proposed	図8は定着ローラベルトから見た状態を示している。
	Baseline	図8には、前述のように、定着ローラで構成されている。
	IBM	図8は、固定しているローラから見られたベルトを見せます。
	REFERENCE	図8はベルトを定着ローラ方向から見た図である。
15	Input	The pressure belt 53 is brought into contact with the fixing roller 51 .
	Proposed	加圧ローラ53と定着ローラ51に当接するようになっている。
	Baseline	加圧ローラ53と定着ローラ51に当接されている。
	IBM	圧力ベルト53が固定しているローラ51に接触させられます。
	REFERENCE	この加圧ベルト53は、定着ローラ51に当接される。
17	Input	Referring now to FIG . 3 , the arrangement of the fixing unit 9 in the longitudinal width direction is described .
	Proposed	図3を参照して、定着装置9の長手方向の幅、配置について説明する。
	Baseline	次に、図3を参照して、定着装置1の長手方向の幅の構成を示すブロック図である。
	IBM	今をイチジクに引き合わせること。3、固定している9号の打ち合わせは、経度の広さ方向で述べられます。
	REFERENCE	次に、定着部9の長手幅方向の配置に関し、図3を参照しつつ説明する。
19	Input	Next , the fixing unit 9 in accordance with the first embodiment is described in conjunction with FIG . 2 .
	Proposed	次に、第1の実施の形態に係る定着装置を図9を用いて説明する。
	Baseline	次に、図2を参照して、実施の形態1に係る定着装置9について説明する。
	IBM	次に、最初の体現に従った固定している9号は、イチジクとともに述べられます。2.
	REFERENCE	次に、この第1の実施形態による定着部9について図2を用いて説明する。
22	Input	The width of the conductor patterns 11a & #x2013; 11d and lead conductors 13 , 14 after fired is set , for example , to about 40 μ m .
	Proposed	焼成は約40μmに設定した後、120、131a-11dとリード導体13及び14のパターン幅を、例えば、3bc#x番の導体である。
	Baseline	導体パターン11a~11dとリード導体13及び14の幅Wは、焼成した後は、例えば、約40μmである。
	IBM	発射したのは約40μmへのセット、例えば、だった後で、案内者の広さは、11a–11dと先頭案内者13、14に基づいて作ります。
	REFERENCE	導体パターン11a~11d及び引き出し導体13、14の焼成後における幅は、例えば40μ程度に設定される。

Input means input Eapanese sentence. Proposed means the output our proposed method. Baseline means the output of moses. IBM means the output of IBM King504 (翻訳の王様). REFERENCE means the correct sentence and handmade.