♦ Recepción/ 22 abril 2019
♦ Aceptación/ 30 junio 2019

A Review on Automatic Machine Translation Approaches

Una revisión sobre los enfoques de traducción automática

Diadeen Ali Hameed[1], Yasir Khalaf Hussein[2], Luay Ibrahim Kalaf [3], B. Rahmatullah[4]

1Department Electronic, Engineering Shrqat Faculty, Tikrit University, Iraq, diaa@tu.edu.iq.
2Department Mathematical, Education Faculty, Tikrit University, Iraq, yasseralhusain@tu.edu.iq
3Department Computer Sconce, Faculty of Computer Sconce and Math., Iraq, luay-ibku@yahoo.com..
4Department Computing, Faculty of Arts, Computing and Creative Industry, Sultan Idris Education university, Malaysia, bahbibi@fskik.upsi.edu.my.

ABSTRACT/ This article explains a distinct approach to the machine translation (MT) framework to translate a text from the source natural language to the target language and reviews the four main approaches to machine translation (rule-based, corpus-based, knowledge-based and hybrid-based) and evaluates current MT technologies with their pros and cons. To conclude our review of the literary works, we observe that the inability of a single machine translation strategy to perform at a satisfactory standard and result in reduced output fluency and quality. In contrast, a hybrid strategy conglomerates the power of two or more methods to create the translation's entire fluidity and quality.
Keyword: language, translate, machine translation, approaches machine translation.
RESUMEN/ Este artículo explica un enfoque distinto del marco de traducción automática (MT) para traducir un texto del lenguaje natural de origen al idioma de destino y revisa los cuatro enfoques principales para la traducción automática (basado en reglas, basado en corpus, basado en conocimiento e híbrido) y evalúa las tecnologías MT actuales con sus ventajas y desventajas. Para concluir nuestra revisión de las obras literarias, observamos que la incapacidad de una sola estrategia de traducción automática para funcionar a un nivel satisfactorio y dar como resultado una fluidez y calidad de salida reducida. En contraste, una estrategia híbrida conglomera el poder de dos o más métodos para crear toda la fluidez y calidad de la traducción.
Palabra clave: idioma, traducir, traducción automática, enfoques de traducción automática.

INTRODUCTION

The MT is a branch of artificial intelligence and natural language processing which is known as an automatic process by a computerized system that converts source text from one natural language to another natural language without human intervention. Translation is a creative process that includes of retrieving the meaning of the authentic text in the translated text. The progress and potential of MT has been debated much through history since the mid–1950s (Agbeyangi, 2015).

Nevertheless, despite the exerted effort, the performance of translation in relation to the quality and context is very low compared with that of human translation, and this shortages in the quality of translation encourages for computerized systems. The solution for the issue of context can be through delimitating the subject domain so that machine utilizesin a narrow area. The MT system would perform badly when give a text outside the area. Existing research emphases on almost approaches based of automatic MT system, result in an extremely specific, task–dependent system.

Translation Models

The term of translation model refers to any computer–based processes that translate a text from source human language to target human language,with human intervention or not (Arefeh, 2017). MT system divided into three main trends:

1) Machine–aided human translation, this way refers to the human translation when does most of the works but uses one or more computer systems, mostly as resources such as spelling checkers and dictionaries, as assistor.
2) Human–aided MT, most of the translation are conducted by computer system but human might possible need for an assistance this is said to be human–assisted machine translation,
3) Automatic machine translation (AMT),it is a type of translation which refers to the process of translation without intervention of human beings.

The purpose behind the translation process is to support users who want to access content in a language in which they are not fluent"(Koehn, 2010). It is necessary to perceive and comprehend the historical development of TM approaches in order to give a precise judgment for its present developments(Stein, 2011).

AUTOMATICMT APPROACHES

Currently, the approaches of MT systems are four main components and each approach may have many sub–approaches, Online MT system used different approaches, It is classified as follows: (Elsherifi, 2017).

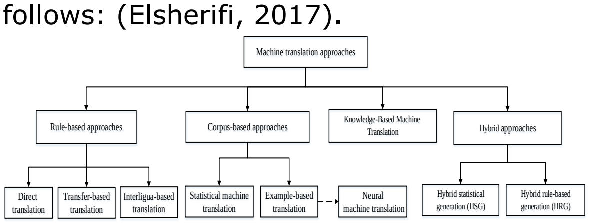

Fig. 1.Structure of MTapproaches

Rule–based Approaches"

Rule–based MT (RBMT): it is considered as the pioneer techniques utilized in the AMT (Al-Taani, 2015), the RBMT employsof representations and linguistically knowledge rules which are able to provide profound analysis for both semantic level and sentence structure but limited to the human written rules (Alqudsi, 2014), presented applications of MT in an overview of the rule–based translation clarifying the need for more research efforts in this approach.

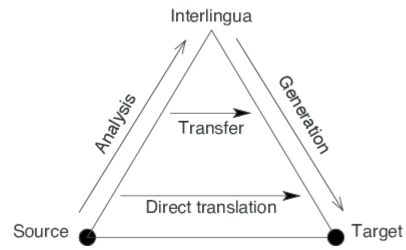

Fig. 2. Bernard Vauquois' pyramid, RBMT model

Direct translation— refers also to binary translation or dictionary–based MT, it is used in the first AMT and prepared to a specific pair of languages in one direction translation with used of dictionaries. (Zantout, 2000). Most of the AMT systems have been adopted on the direct translation, it designed for a particular language pair.Algorithm of direct translation consists of the following:

1) Morphological analysis – analysis of source language and identification of limited to problems of input text, it is depends on source language grammar.
2) Bilingual dictionary lookup – the most common approach was to augment the relevant source language dictionary entries with contextual information or with directions for structure changes.
3) Local reordering–arrange the sentence in the target language, it is depends on target language grammar.

Scholars have found that the ability of linguistic analysis of the source language is lacking in direct approach and cannot remedy the complication of natural language "(Farghaly, 2012).

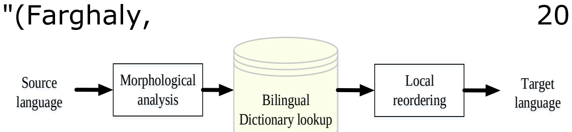

Fig. 3. Direct MT approach

Transfer–based MT— (TBMT) was invented in order to preserve meaning whilst translating. TBMT has three steps; transfer, generation and analysis. (Diego, 2018). This approach encountered several problems:

1) The difficulty of establishing interlingua elements and there was little success with lexical equivalence.
2) In the process of abstraction to language–independent representation too much information was lost about text–oriented structure."
3) "During the translation process, it uses three dictionaries: two monolingual dictionaries (source language and target language) and a bilingual dictionary with a mapping of the source languages and target languages "(Chéragui, 2012).
4) Shaalan (2013), presented the usage of transfer–based approach developing bi–directional MT system.The main components of transfer MTapproach are:
    1) Source languageanalysis.
    2) Source language representation.
    3) Transfer from language of source to language of destination.
    4) Representation of the target language.
    5) Target language for synthesis.
    6) Three dictionaries (source linguistic dictionary & grammar, dictionary source / target, and dictionary & grammar target language)

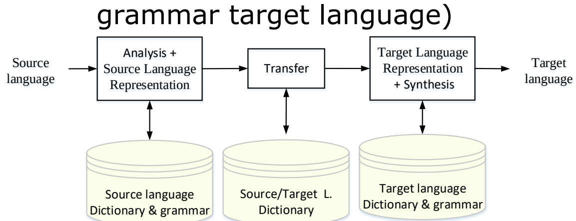

Fig. 4. Transfer MT approach

Interlingua Translation– The interlingua approach originated from the weaknesses of the direct approach; and the translation of the meaning of the phrase and this implied translation through conceptual representation; the other reason was the creation of multilingual MT; various suggestions were put forward for interlingua::

1) Logical language creation.
2) Adoption of the natural or artificial language that exists.

Interlingua MT strategy is a typical two-stage indirect approach job:

1) scrutinize the phrases of the source language into an intermediate representation (interlingua representation),
2) produce the text of the target phrases by changing the significance of the representation.

The intermediate representation of the source and target language is language independent "Universal", therefor interlingua MT approach was used in systems that boost numerous languages (Shaalan, 2006). and these different approaches continue to the present.

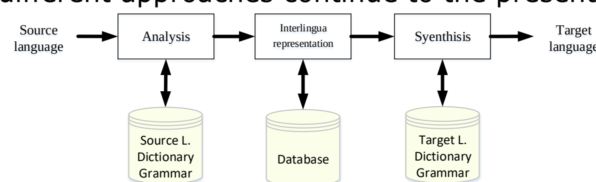

Fig. 5. Interlingua MT approach

B. Corpus–based Approaches

Statistical MT (SMT) – Brow created the layered mathematical models of the translation process, arguing that these models could be statistically educated from what is known as the parallel corpora. Parallel corpora are collections of documents that have been translated from the source language to the target language, sentence by sentence. SMT the phrase-based strategy in particular (Koehn, 2003), advances fast since the beginning at last 20 years (Yamada, 2001, Och, 2002, Chiang, 2008, Huang, Chiang, 2007, Koehn, 2017, Watanabe, 2007, Chiang, 2008, Galley, 2008, Hopkins, 2011, Cherry, 2013, Galley, 2013).

Simply, the SMT works when we have the parallel corpora, we know that each word in the source language may have more than one word in the dictionary, and the process of choosing exactly the most suitable word that have a relative meaning to the context as the source one. We find all the combinations of words, and search for each resulted sentence of them in the parallel corpora, according to the number of sentences that are in the corpora and have the set of ordered words in the sentence.

Dividing the number of sentences retrieved on the number of sentences in the parallel corpora, we get a probability, these probability calculated give us an indication in the number of occurrences of a sentence, the higher the probability the higher the chance that this sentence is strongly related to the context (Al–Taani, 2005).SMT is still seldom adopted in the professional translation circle because its outputs are usually poor and far from satisfactory.

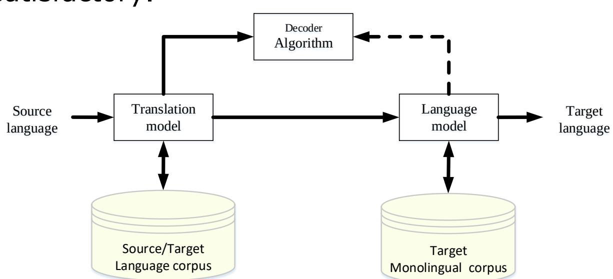

Fig. 6. Structure SMT

Neural MT (NMT)is also a statistical paradigm, NMT is one of the new approach, that utilizes a very enormous artificial neural network to forecast the probability of words sequence, NMT system processes -multiple (instead of just one) neural network layers. Google translate and Facebook announced their shift from statistical MT system paradigm to a new NMT system

Example–based MT (EBMT) - Makoto Nagao (1984), proposed this example–based approach or (memory–based approach), knowledge based approach depends on MT using similarity without the linguistic knowledge depending on the use of enormous bilingual corpus with parallel texts at actual time"(Elsherif, 2017). EBMT is one of the types of corpus–based approaches, it store the data In the form of example sentences. Approaches imitate a basic memory technique (analogy) of human translators and is akin to filling the database of a translation memory system"(King, 2001). Development of EBMT systems depended on the bilingual database (knowledge base).EBMT approach depends to memory techniques, it requires large physical memory and despite of the MT community's movement towards this translation method, it is easily combined and quite interesting with the others (Diego, 2018). The EBMT comprises of three stages:

1) Matcher, determine the main phrase of the input text (source language), that counterpart the example–base system (Bi–Lingual Corpus).
2) Identification module, involves finding equivalent translation of the matched phrase.
3) Recombination module, is constructing the text by combining the phrase parts into one sentence and combining the sentences into one text. (Zitouni,2014).

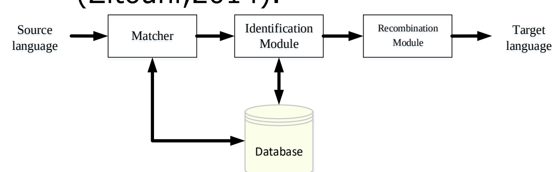

Fig. 7.Structure EBMT approach

Knowledge–based MT (KBMT)"- Increase MT quality by decreasing ambiguity as one of the main MT system issues by increasing profound source language analysis of text significance, this strategy can be used in the process of interpreting text using knowledge bases as a reference offering language-independent representation significance of the phrase section (Alqudsi, 2014). KBMT systems require extensive understanding of source, target language and system environment (El–Shishtawy, 2014).

Shaalan(2012), suggest that the KBMT system is using knowledge bases approach to learn translation rules form positive examples and negative, and using a small amount of parallel phrases (Soudi, 2012). While the use of WordNet and Wikipedia in different research areas is increasing such as NLP and information retrieval (Mohamed,2011, Saad, 2013).

Hybrid-based MT(HBMT) - in recent years, many new appeared of HBMT approaches. HMT system combined the strengths of both rule–based approach and corpus–based approaches methodologies (Hatem, 2017), and it is divided into two main parts:

First: hybrid statistical generation (HSG), when the statistical approaches do most of the work but uses one or more rule–based approaches, mainly as assist resources. HSG is a combination of the statistical approach and one or more rule–base MT approaches.

Second: hybrid rule–based generation (HRG), when the rule–based approaches does most of the work but uses one or more corpus–based approaches, mainly as assist resources. HRG approach is a combination of the rule–based method and the statistical approach or example–based or both approaches.

The aim of HBMT system architectures is to provide better translation of both paradigms (Hunsicker, 2012). Researchers continue to use the HMT System to address the different issues in this region "(Bakr, 2008, Tachicart, 2014). The HMT strategy includes a forest-based model, a syntax-based model, a phrase-based model, and a word-based model.

1) Word-based models also acknowledged as alignment models differ in two aspects: the originality of the cardinal connection between the source and the target words and the dependence assumptions developed in this mapping. One of their general inadequacies is that they are primarily intended among specific words to model the lexical dependencies. They are unable to reorder phrases over long distances. Therefore, phrase-based models have been provided.

2) Phrase-based models have been provided to mitigate word-based model deficiencies by presenting sentences as the fundamental translation unit (Och, 2003). Regardless of this model's section, local reordering, translation of brief phrases, or deletion and insertions that are sensitive to the local context are possible. They are thus a strong and simple machine translation process. Other phrase-based methods mechanism is the use of a beam-search strategy to decode the phrase section. Although the notable ability of phrase-based models to reduce constraints of word-based models, they still have their constraints, one of which is the incapacity of long-distance modeling of source word reordering. This model failure led in syntax-based models being produced.

3) **Syntax-based model** is the natural language sentence graded structure. Syntax-based models can be classified into two broad classes based on the type of input: the tree-based system and string-based systems.

a. **String-based systems**–These are MT systems with a string input to be simultaneously translated and parsed by synchronous grammar (Galley et al, 2006).

b. **Tree-based systems**–Using two separate steps, they perform translation: decoding and parsing. Tree-based systems generate some beautiful features. High speed decoding (linear time vs. cubic time, do not involve a binary-branching grammar as in string-based models, and have distinct grammars for translation and parsing) are among these features (Riesa, 2006). Despite the advantages of tree-based schemes, they are subjected to significant deficiencies: they only use the 1st parse tree to guide the translation, which may be translation errors due to parsing errors (Quirk and Oliver, 2006). The aim behind extending tree-based scheme to forest-based MT is to palliate translation and parsing error sparseness.

c. Forest-based translation is a compromise between tree-based techniques and string-based systems, as it combines both methods ' benefits. Forest-based translation promotes quicker decoding and soothes parse mistakes. Forest-to-string conversion is an expansion of the tree-to-string model as it utilizes a filled parse forest as a string input and output (Miet al, 2008). Cmejrek (2014) suggested a forest rearrangement model to cope with all the different meanings of the vague forest input and word order distinctions in MT. Heinterduced an unprecedented expansion of a forest-to-string machine translation system with a rearrangement model.

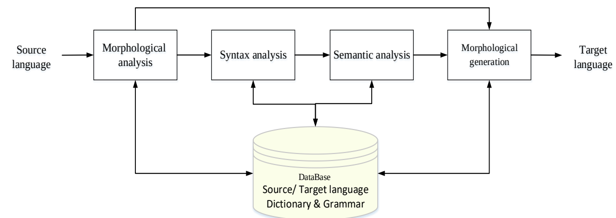

Fig.8.Structure of HMT approach

CHALLENGES OF MT APPROACHES

There are many of stylistic and structural differences among languages, which make automatic machine translation a very difficult task. Overview the some of these problems are as follows:

A. Challenges of RBMT

1. Experts formulate rules.
2. Hard to keep and stretch.
3. Ineffective for phenomena of management.
4. In general translation systems, the amount of regulations will increase dramatically.

B. Challenges of KBMT

1. Difficult to construct hierarchy of understanding.
2. Difficult to identify information granularity.
3. Difficult to portray knowledge.
4. Hybrid translation results.

C. Challenges of EBMT,

1. The measure of similarity is system delicate.
2. The price of searching is greater.
3. The issue of acquiring knowledge still persists.

D. Challenges of SMT

1. No background in linguistics.
2. The cost of searching is costly.
3. Difficult to capture phenomena of long range.
4. Need a huge quantity of corpora parallel.
5. Due to corporate insufficiency, the quality of the translation will be very rough.

MOTIVATION OF MT APPROACHES

The motivation of the paper was to summarize all techniques, classifications and requirements that were available. This overview would allow academics to select the appropriate translation model on language resource evaluation, language richness versus paradigm requirement for a particular language weighting.

V. MOTIVATION OF MT APPROACHES

The paper's motive was to summarize all accessible methods, classifications and specifications. This overview would allow academics to select the relevant translation model for a particular language weighting on language resource assessment, language richness versus paradigm necessity.

A. Motivation of RBMT

1. Building an original scheme is easy.
2. Based on the theories of language.
3. Effective for phenomena of the heart.
4. Better domain-specific translation selection.
5. Translation quality is useful for particular domain systems.

B. Motivation of KBMT

1. Based on knowledge taxonomy.
2. Contains engine of inference.
3. Representation of Interlingua.

C. Motivation of EBMT

1. Extracts corpus knowledge.
2. Based on corpus translation patterns.
3. Reduces the expense of man.

D. Motivation of SMT

1) Does not consider language grammar for translation,
2) Extracts knowledge from corpus,
3) Reduces the human errors,
4) Model is mathematically grounded.

Motivation of HBMT is better than single approach for morphological divergent and huge language.HMT of translation system can exceed many baseline translation systems depended on EBMT, RBMT, KBMT and SMT approaches individually.

MACHINE TRANSLATION TECHNOLOGY

Translation goals are to support users who need to access content in a language in which they are not familiar or fluent (Koehn, 2010). All MT system share in one general structure, it is divide into two main parts.

A. Source Language Analysis

There are different MTt**echnology** used one or more in morphological, syntactic, and semantic of source language analysis, as shown in the fig. 9 below.

Approaches	Morphological	Syntactic	Semantic
DMT	X		
TMT		X	
IMT		X	X
SMT			X
EBMT	X		X
HBMT	X	X	X

Fig. 9. Source language model for MT approach (Diego, 2018)

B. Target Language Generation

There are different approaches used one or more in morphological, syntactic, and semantic of target language generation, as shown in the fig. 10 below.

Approaches	Morphological	Syntactic	Semantic
DMT	X		
TMT		X	X
IMT		X	X
SMT			X
EBMT			X
HBMT	X		

Fig. 10. Target language model for MT approach (Diego, 2018)

VII. CONCLUSION

MT systems overview of the available MT methods developed since the mid-1950s and use a single strategy does not attain an acceptable performance because they are inflexible and inconsistent for large-scale implementation and provide a superficial representation of information leading to reduced quality and output fluency. In addition, MT's hybrid strategy combines the power of two or more approaches to developing the quality of the entire machine translation. Future scientists should therefore concentrate more on MT using two or more methods in order to improve and develop the quality of machine translation.

REFERENCE

[1] Agbeyangi, Abayomi O., EludioraSafiriyu I., Adenekan, Olujide A., (2015), "English to Yorùbá Machine Translation System using Rule-Based Approach", Journal of Multidisciplinary Engineering Science and Technology (JMEST) ISSN: 3159-0040 Vol. 2 – 2015

[2] ArefehKazemi a ,Antonio Toral b , Andy Way c , AmirhassanMonadjemi a , MohammadaliNematbakhsh , "Syntax and semantic-based reordering in hierarchical phrase-based statistical machine translation", Expert Systems With Applications 84 (2017), 186-199

[3] Koehn, Philipp. 2010. Statistical Machine Translation. Cambridge University Press.

[4] Huck, M.; Vilar, D.; Stein, D.; and Ney, H. (2011). Advancements in Arabic-to-English hierarchical machine translation, In Preoceeding of the 15th Conference of the European Association for Machine Translation, Leuven, Belgium: European Association for Machine Translation, 273-280.

[5] Hatem M. Elsherifi, Tariq Rahim Soomro, 2017, Perspectives of Arabic machine translation, Journal of Engineering Science and Technology September 2017, Vol. 12 (9)

[6] Ahmad Farhat and Ahmad Al-Taani , 2015, A Rule-based English to Arabic Machine Translation Approach , The International Arab Conference on Information Technology (ACIT'2015).

[7] Alqudsi, A.; Omar, N.; and Shaker, K. (2014). Arabic machine translation: A survey. Artificial Intelligence Review, 42, 549-572.

[8] M. A. Chéragui, Theoretical over view of machine translation, Proceedings ICWIT (2012) 160.

[9] Shaalan, K. (2013). A survey of named entity recognition and classification. Computational Linguistics, 40(2), 471-510.

[10] Zantout, R.,Guessoum, A. (2000). Arabic machine translation: A strategic choice for the Arab World. Journal of King Saud University - Computer and Information Sciences, 12, 117-144.

[11] Soudi, A.; Farghaly, A.; Neumann, G.; and Zbib, R. (2012). Challenges for Arabic machine translation. Amsterdam, Netherlands: John Benjamins Publishing.

[12] Diego Moussallema, b, Matthias Wauera, Axel-CyrilleNgongaNgomob, (2018), Machine Translation using Semantic Web Technologies:

A Survey, 2018 Elsevier B.V.All rights reserved.

[13] Shaalan, K., A. Abdel Monem and A. Rafea, 2006. Arabic morphological generation from interlingua. Proceeding of the Intelligent Information Processing III, IFIP TC12 International Conference on Intelligent Information Processing, Sept. 20-23, Springer, Boston, pp: 441-451.

[14] P. Koehn, F. J. Och, D. Marcu, Statistical phrase-based translation, in: Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1, Association for Computational Linguistics,2003,pp.48–54.

[15] Yamada, K., Knight, K., 2001. A syntax-based statistical translation model. In: Proceedings of the 39th Annual Meeting on Association for Computational Linguistics. Association for Computational Linguistics, pp. 523–530.

[16] P. Koehn, F. J. Och, D. Marcu, Statistical phrase-based translation, in: Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1, Association for Computational Linguistics,2003,pp.48–54.

[17] Chiang, D., Marton, Y., Resnik, P., 2008. Online large-margin training of syntactic and structural translation features. In: Proceedings of the conference on empirical methods in natural language processing. Association for Computational Linguistics, pp. 224–233.

[18] Huang, L., Chiang, D., 2007. Forest rescoring: Faster decoding with integrated language models. In: Annual Meeting Association For Computational Linguistics. Vol. 45. p. 144.

[19] O. Bojar, R. Chatterjee, C. Federmann, Y. Graham, B. Haddow, S. Huang, M. Huck, P. Koehn, Q. Liu, V. Logacheva, et al., Findings of the 2017 conference on machine translation (WMT17), in: Proceeding soft he Second Confemrence on Machine Translation, 2017,pp.169– 214.

[20] Watanabe, T., Suzuki, J., Tsukada, H., Isozaki, H., 2007. Online large-margin training for statistical machine translation. In: In Proc. of EMNLP. Citeseer.

[21] Chiang, D., Marton, Y., Resnik, P., 2008. Online large-margin training of syntactic and structural translation features. In: Proceedings of the conference on empirical methods in natural language processing. Association for Computational Linguistics, pp. 224–233.

[22] Galley, M., Manning, C. D., 2008. A simple and effective hierarchical phrase reordering model. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, pp. 848–856.

[23] Hopkins, M., May, J., 2011. Tuning as ranking. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, pp. 1352–1362.

[24] Cherry, C., 2013. Improved reordering for phrase-based translation using sparse features. In: HLT-NAACL. pp. 22–31.

[25] Galley, M., Quirk, C., Cherry, C., Toutanova, K., 2013. Regularized minimum error rate training. In: EMNLP. pp. 1948–1959.

[26] D.D. King, R.J. Redpath, Method and system for improving machine translation accuracy using translation memory, US Patent 6,278,969, (2001).

[27] AhmadT. Al-Taani and Eyad M. Hailat, (2005), "A Direct English-ArabicMachine Translation System", Information Technology Journal 4(3) pages 256-261.

[28] Zitouni, I. (2014). Natural language processing of semitic languages, Springer.

[29] Bakr, H.M.A.; Shaalan, K.; and Ziedan, I. (2008). A hybrid approach for Perspectives of Arabic Machine Translation 2331 Journal of Engineering Science and Technology 2017, Vol. 12(9)

[30] Tachicart, R.; and Bouzoubaa, K. (2014). A hybrid approach to translate Moroccan Arabic dialect, In Intelligent systems: Theories and applications (sita-14), 2014 9th international conference, Rabat, Morocco: IEEE., 7-8.

[31] Soudi, A.; Farghaly, A.; Neumann, G.; and Zbib, R. (2012). Challenges for Arabic

machine translation. Amsterdam, Netherlands: John Benjamins Publishing.

[32] Shaalan, K.; and Hossny, A.H. (2012). Automatic rule induction in Arabic to English machine translation framework, In Challenges for Arabic Machine Translation, Amsterdam, Netherlands: John Benjamins Publishing, 135-154.

[33] Mohamed I. Eldesouki.; Arafa, W.; Darwish, K.; and Gheith, M. (2011). Using wikipedia for retrieving Arabic documents, In Proceedings of Arabic Language Technology International Conference (ALTIC), Alexandria, Egypt.

[34] Saad, M.; Langlois, D.; and Smaïli, K. (2013). Extracting comparable articles from Wikipedia and measuring their comparabilities. Procedia - Social and Behavioral Sciences, 95, 40-47.

[35] Galley, M.; Graehl, J.; Knight, K.; Marcu, D.; DeNeefe, S.; Wang, W.; and Thayer, I. (2006). Scalable inference and training of context-rich syntactic translation models, In Proceedings of the 21st International Conference on Computational Linguistics and the 44th annual meeting of the Association for Computational Linguistics, Association for Computational Linguistics, 961-968.

[36] Hunsicker, S.; Yu, C.; and Federmann, C. (2012). Machine learning for hybrid machine translation, In Proceedings of the Seventh Workshop on Statistical Machine Translation, Association for Computational Linguistics, 312-316.

[37] Quirk, C. &Corston-Oliver, S. (2006). The impact of parse quality on syntactically-informed statistical machine translation. In proceedings of Conference on Empirical Methods in Natural Language Processing, pp. 56-63.

[38] Miet, H., Liang, H. & Liu, Q. (2008): “Forest-based translation”. In Proceedings of Association of Computational Linguistic, pp. 192–199.

[39] Cmejrek, M. (2014). Reordering Model for Forest-to-String Machine Translation. In proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, pp. 227–232.

[40] John Oladosu, AdebimpeEsan, Ibrahim Adeyanju, Benjamin Adegoke, OlatayoOlaniyan and BolajiOmodunbi, "Approaches to Machine Translation: A Review ", FUOYE Journal of Engineering and Technology, Volume 1, Issue 1, September 2016.

[41] Benson Kituku, Lawrence Muchemi, WanjikuNganga, "A Review on Machine Translation Approaches", Indonesian Journal of Electrical Engineering and Computer Science Vol. 1, No. 1, January 2016, pp. 182-190.

[42] J. Riesa, B. Mohit, K. Knight, and D. Marcu, “Building an English-Iraqi Arabic Machine Translation System for Spoken Utterances with Limited Resources'', In the Proceedings of INTERSPEECH, Pittsburgh, USA, 2006.