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# WSNNet: Multimodal Stacked Bidirectional LSTM with Attentions for Indoor Localization of Wireless Sensor Network

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**ABSTRACT** As verified experimentally, this new proposal represents a significant improvement in accuracy, computation time, and robustness against outliers.

**INDEX TERMS** Enter key words or phrases in alphabetical order, separated by commas. For a list of suggested keywords, send a blank e-mail to keywords@ieee.org or visit http://www.ieee.org/organizations/pubs/ani_prod/keywrd98.txt

## I. INTRODUCTION

SIMULTANEOUS Localization and Mapping(SLAM) is widely used in autonomous vehicles, drones, intelligence field robots, and mobile phone applications. Thus, according to the smart city development plan, several technologies are required in such a way that the demand and the necessity of SLAM increase together. Various kinds of sensors are utilized to SLAM, such as GPS, LiDAR, ultrasonic-based sensor, camera and distance sensor. Especially, trilateration algorithm has been widely incorporated into robotics fields, especially utilized in the indoor environment to estimate the position of an object by distance measurements obtained from range sensors such as UWB, ultrasonic, laser-based beacon sensors [1]–[3] due to the convenience of trilateration that estimates the position of a receiver of range sensors if one only knows range measurement. For that reasons, range-only Simultaneous Localization and Mapping(RO-SLAM) methods are utilized popularly, which not only estimate the position of the receiver of range sensors, but also localize the position of range sensors regarded as features on a map, and studies have been conducted continuously in terms of probability-based approach [4]–[7].

In the meantime, as deep learning age has come [8], various kinds of deep neural architectures have been proposed for many tasks related to robotics field, such as detection [9]–[11], navigation [12], [13], pose estimation [14], and so on. Especially, recurrent neural networks (RNNs), originated from Natural Language Process(NLP) area [15], have been shown to achieve better performance in case of dealing with time variant information, thereby RNNs are widely utilized such as not only speech recognition, but also pose estimation and localization [14], [16]–[19].

In this paper, we propose a deep learning-based SLAM method by multimodal stacked bidirectional Long Short-Term Memory(multimodal stacked Bi-LSTM) for more accurate localization of the robot. Using deep learning, our structure directly learns the end-to-end mapping between range measurements and robot position. This operation non-linearly maps the relationship not only considering the long-range dependence of sequential distance data by the LSTM, but also using the correlation of the backward information and the forward information of the sequence of each time step by virtue of its bidirectional architecture. Existing RO SLAM needs calibration before filtering, and then, range measurement undergoes outlier rejection, prediction and correction processes are needed. Furthermorme, it uses low dimensional data to perform localization, there is a disadvantage that estimation is difficult even if the value deviates slightly from the model. Therefore, we solve this complex algorithm with end-to-end based deep learning. This system overview is shown in the figure below.

Various kinds of sensors have been utilized to localize a object using range measurement sensors, such as GPS, ultrasonic-based sensors. ultra-wideband(UWB) sensors. However, almost distance measured by range measurement sensors are based on Time of Flight(TOF), Time of Arriaval(TOA) [20], or Time of Differential Arrival(TDOA) in such a way as to consist of the 1-D data composed by the distance between landmarks and robot. This is the main issue dealing with range measurments, called *rank-dificiency* problems. Besides, only mangitudes could represent the range measurement, deflection, reflection, and refraction and ic Because range measurements consist of

In contrast to other SLAM, RO SLAM suffer from "rank deficiency problem", which means range measurement is 1D data so it is too deficient to describe position or orientation as you guys knows, it only has magnitude. As this figure shown, in 3D, posiibility of location of sensor is distributed over sphere / since range measurement doesn't contain direction information! To solve this problem, various type of RO SLAM has been studied. RO SLAM is generally divided into two approaches; PF RO SLAM and KF based RO SLAM

. We also provide statistical analysis from simulations demonstrating that our new approach can cope with highly noisy sensors and reduces in one order of magnitude the average errors of the method proposed

The rest of the paper is organized as follows. Section 2 describes relevant localization methods. Section 3 introduces principals of neural networks. The experiments by which these methods will be compared are given in Section 4. The results will be discussed in Section 5, and concluding comments will be made in Section 6

## II. RELATED WORKS

To localize nodes of the range measurement sensors on the indoor space while covering range measurements' uncertainties using neural networks, several fascinating works have been studied. Regarding previous proposals, Chenna *et al.* first shows the suitability that Kalman filter could be replaced with the RNN when estimating states and tracking nodes [21]. However, they did not provide numerical analysis, so Shareef *et al.* do [22] and conduct their experiment in the real-world. They conlcude Multi-Layer Perceptron(MLP) may be the best option among the suggested Kalman filter models and RNN. Similarly, many researchers also had achived considerable improvement to localize position of mobile node by exploiting MLP [23]–[25]. Note that their In case of [22]. They let MLP learn the relationships between range measurement and position of mobile node, yet MLP could not learn sequential modeling. MLP just learn the relationship like generating finger print map.

First, In case of particle filter based RO SLAM, it is more robust than kalman filter based approach, As figure illustrated, you can observe how the Kalman filter based approach performs poorly / when the uncertainty in the beacon position becomes excessively large. And In PF filter based RO SLAM, they exploit Rao-Blackwellization. Rao-blackwellization is a mathematical method. By dividing one hidden states into two variable, it proves that variance can be reduced.

So they utilize rao-blackwellized particle filter, called RBPF, so many authors separate all states / into states of landmarks and state of robot. But in many cases, they just consider almost annular ambiguity or projected spherical ambiguity, not spherical ambiguity!.

On the other hand, kalman filter based approach is steadily studied, and they make efforts to reduce the number of hidden state variables. In case of 3D RO SLAM, there are two angles to be estimated, one is the azimuth angle that indicates angle on horizontal plane, and the other is elevation angle which indicates amount of elevation literally. On state of the art paper about 3D RO SLAM based on EFK, they dramatically reduce the number of hidden states by expressing the hypothesis as multiplication of probability about azimuth angle and elevation angle as this figure shown.

Besides, not only for the indoor environment, also on the underwater environment, Olson *et al.* suggest a method for localize a autonomous underwater vehicle(AUV) using extended Kalman Filter(EKF) [26].

Especially, deep learning-based approaches are also implemented to reduce noise of the san

First, it's very noisy, so it can occur errors easily. Second, the measurement is very ambiguous because each measurement is defined as the probability density of the sensor's potential position. The last problem is that the landmark location estimations may converge to multi-modal densities. Especially, trilateration algorithm has been widely incorporated into robotics fields, especially utilized in the indoor environment to estimate the position of an object by distance measurements obtained from range sensors such as UWB, ultrasonic, laser-based beacon sensors [1]–[3] due to the convenience of trilateration that estimates the position of a receiver of range sensors if one only knows range measurement. For that reasons, range-only Simultaneous Localization and Mapping(RO-SLAM) methods are utilized popularly, which not only estimate the position of the receiver of range sensors, but also localize the position of range sensors regarded as features on a map, and studies have been conducted continuously in terms of probability-based approach [4]–[7].

In robotics fields, Blanco SLAM is a technique for building the map information while localizing the position of the robot while moving. Localization of the SLAM predicts the current position of the robot using the landmark measured by the sensor, and mapping locates the terrain object based on the pose of the robot. Research on this technology has been actively carried out, and researches and techniques have been summarized. In 2006, the ad hoc sensor network consisting of range detection beacon was applied to SLAM technology for various ranges. This technology integrates node-to-node measurements to reduce drift and expedite node-map convergence [27] In 2008, the technique to consistently combine the observation information considering the uncertainty was studied through comparing the experimental data with the actual robot and simulation using Ultra Wide-Band (UWB) devices and Rao-Balckwellized Particle Filter (RBPF) [4]. In 2012, a simple and efficient algorithm for position recognition with high accuracy and low computational complexity was researched with ultrasonic sensors [28]. In recent years, 3-dimensional-based SLAM has also been under active research and development. In 2013, a localization mapping approach of a wireless sensor network (WSN) node was studied through a centralized EKF-SLAM-based optimization research [6]. In addition, in 2014, a method of minimizing noise and localizing Unmanned Aerial Vehicle (UAV) by using range-only measurement while simultaneously mapping the position of the wireless range sensors were proposed [29]. SLAM based on range measurement has been continuously researched and developed then applied to various fields. In this paper, we propose a novel technology that applying deep-learning to range-only SLAM that derives accurate range and robot position measurement through in-depth learning.

### A. DEEP LEARNING FOR LOCALIZATION

There have been many approaches combining Simultaneous Localization and Mapping (SLAM) with deep learning, aiming to overcome the limitations on SLAM only technique such as difficulty on tuning the proper parameters in different environments and recovering an exact scale. Actually, those researches are showing the superior performance to the traditional SLAM approaches.

One of the popular SLAM techniques with deep learning is CNN-SLAM [30] which takes Convolutional Neural Networks (CNNs) to precisely predict the depth from a single image without any scene-based assumptions or geometric constraints, allowing them to recover the absolute scale of reconstruction. Another approach using deep learning for localization is Deep VO [31] In this method, Recurrent Convolutional Neural Networks (RCNNs) is utilized. Specifically, feature representation is learned by Convolutional Neural Networks and Sequential information and motion dynamics are obtained by deep Recurrent Neural Networks without using any module in the classic VO pipeline.

### B. APPLICATIONS OF LSTMS

There are many variations of LSTM architecture. As studies of deep learning are getting popular, various modified architectures of LSTM have been proposed for many tasks in a wide area of science and engineering. Because LSTM is powerful when dealing with sequential data and infering output by using previous inputs, LSTM is utilized to estimate pose by being attached to the end part of deep learning architecture [17]–[19] as a stacked form of LSTM. In addition, LSTM takes many various data as input; LSTM is exploited for sequential modeling using LiDAR scan data [16], images [14], [17], IMU [32], a fusion of IMU and images [31]. Since existing RO-SLAM performs localization using low-dimensional data, it is difficult to estimate even if the value deviates slightly from the model. In addition, LSTM has the advantage of being able to solve long-term dependence problem of traditional RNN, and it is possible to model it by non-linear mapping through analyzing the current situation without modeling data characteristics separately. Therefore, we propose RO SLAM technology using deep learning based SLAM which applies the advantages of LSTM and deep learning to solve the disadvantages of RO SLAM.

### C. ATTENTION

*Attention* is powerful module nowadays and mostly improves performance of neural network. Originally neural networks treats information equally. But, using attention layer, neural networks can be ATTENDED what it should be examined closely. At the first time, attention is utilized at natural language processing area for improving translation performance [33]. But nowadays, attention layer is employed in many areas to improve the performance of the networks. For example, Jaderbeg *et al.* [34] introduced the attention layer to let the neural networks attend to spatial information. In addition, attention is even utilized to pose estimation and optimization [35], detection [36], and video captioning [37]

## III. GUIDELINES FOR GRAPHICS PREPARATION AND SUBMISSION

### A. TYPES OF GRAPHICS

The following list outlines the different types of graphics published in IEEE journals. They are categorized based on their construction, and use of color/shades of gray:

#### 1) Color/Grayscale figures

Figures that are meant to appear in color, or shades of black/gray. Such figures may include photographs, illustrations, multicolor graphs, and flowcharts.

#### 2) Line Art figures

Figures that are composed of only black lines and shapes. These figures should have no shades or half-tones of gray, only black and white.

#### 3) Author photos

Head and shoulders shots of authors that appear at the end of our papers.

#### 4) Tables

Data charts which are typically black and white, but sometimes include color.

## IV. WSN NET

#### 1) LSTM

LSTM is a type of Recurrent Neural Networks(RNNs) that has loops so that infer output based on not only the input data,

TABLE 1: Units for Magnetic Properties

| Symbol | Quantity | Conversion from Gaussian and CGS EMU to SI [a] |
|---|---|---|
| $\Phi$ | magnetic flux | 1 Mx $\rightarrow 10^{-8}$ Wb $= 10^{-8}$ V·s |
| $B$ | magnetic flux density, magnetic induction | 1 G $\rightarrow 10^{-4}$ T $= 10^{-4}$ Wb/m$^2$ |
| $H$ | magnetic field strength | 1 Oe $\rightarrow 10^3/(4\pi)$ A/m |
| $m$ | magnetic moment | 1 erg/G = 1 emu $\rightarrow 10^{-3}$ A·m$^2$ $= 10^{-3}$ J/T |
| $M$ | magnetization | 1 erg/(G·cm$^3$) = 1 emu/cm$^3$ $\rightarrow 10^3$ A/m |
| $4\pi M$ | magnetization | 1 G $\rightarrow 10^3/(4\pi)$ A/m |
| $\sigma$ | specific magnetization | 1 erg/(G·g) = 1 emu/g $\rightarrow$ 1 A·m$^2$/kg |
| $j$ | magnetic dipole moment | 1 erg/G = 1 emu $\rightarrow 4\pi \times 10^{-10}$ Wb·m |
| $J$ | magnetic polarization | 1 erg/(G·cm$^3$) = 1 emu/cm$^3$ $\rightarrow 4\pi \times 10^{-4}$ T |
| $\chi, \kappa$ | susceptibility | $1 \rightarrow 4\pi$ |
| $\chi_\rho$ | mass susceptibility | 1 cm$^3$/g $\rightarrow 4\pi \times 10^{-3}$ m$^3$/kg |
| $\mu$ | permeability | $1 \rightarrow 4\pi \times 10^{-7}$ H/m $= 4\pi \times 10^{-7}$ Wb/(A·m) |
| $\mu_r$ | relative permeability | $\mu \rightarrow \mu_r$ |
| $w, W$ | energy density | 1 erg/cm$^3$ $\rightarrow 10^{-1}$ J/m$^3$ |
| $N, D$ | demagnetizing factor | $1 \rightarrow 1/(4\pi)$ |

Vertical lines are optional in tables. Statements that serve as captions for the entire table do not need footnote letters.

[a]Gaussian units are the same as cg emu for magnetostatics; Mx = maxwell, G = gauss, Oe = oersted; Wb = weber, V = volt, s = second, T = tesla, m = meter, A = ampere, J = joule, kg = kilogram, H = henry.

but also the internal state formed by previous information. In other words, while the RNN deals with sequential data, the network has remembered the previous state generated by past inputs and might be able to output the present time step via internal state and input, which is very similar to filtering algorithms.

However, RNNs often have a *vanishing gradient problem*,i.e., RNNs fail to propagate the previous matter into present tasks as time step gap grows by. In other words, RNNs are not able to learn to store appropriate internal states and operate on long-term trends. That is the reason why the Long Short-Term Memory (LSTM) architecture was introduced to solve this long-term dependency problem and make the networks possible to learn longer-term contextual understandings [38]. By virtue of the LSTM architecture that has memory gates and units that enable learning of long-term dependencies [39], LSTM are widely used in most of the deep learning research areas and numerous variations of LSTM architecutres have been studied.

### A. MULTIPART FIGURES

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Format and save your graphics using a suitable graphics processing program that will allow you to create the images as PostScript (PS), Encapsulated PostScript (.EPS), Tagged Image File Format (.TIFF), Portable Document Format (.PDF), Portable Network Graphics (.PNG), or Metapost (.MPS), sizes them, and adjusts the resolution settings. When submitting your final paper, your graphics should all be submitted individually in one of these formats along with the manuscript.

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Most charts, graphs, and tables are one column wide (3.5 inches/88 millimeters/21 picas) or page wide (7.16 inches/181 millimeters/43 picas). The maximum depth a graphic can be is 8.5 inches (216 millimeters/54 picas). When choosing the depth of a graphic, please allow space for a caption. Figures can be sized between column and page widths if the author chooses, however it is recommended that figures are not sized less than column width unless when necessary.

There is currently one publication with column measurements that do not coincide with those listed above. Proceedings of the IEEE has a column measurement of 3.25 inches (82.5 millimeters/19.5 picas).

The final printed size of author photographs is exactly 1 inch wide by 1.25 inches tall (25.4 millimeters $\times$ 31.75 millimeters/6 picas $\times$ 7.5 picas). Author photos printed in editorials measure 1.59 inches wide by 2 inches tall (40 millimeters $\times$ 50 millimeters/9.5 picas $\times$ 12 picas).

### D. RESOLUTION

The proper resolution of your figures will depend on the type of figure it is as defined in the "Types of Figures" section. Author photographs, color, and grayscale figures should be at least 300dpi. Line art, including tables should be a minimum of 600dpi.

### E. VECTOR ART

In order to preserve the figures' integrity across multiple computer platforms, we accept files in the following formats: .EPS/.PDF/.PS. All fonts must be embedded or text converted to outlines in order to achieve the best-quality results.

### F. COLOR SPACE

The term color space refers to the entire sum of colors that can be represented within the said medium. For our purposes, the three main color spaces are Grayscale, RGB (red/green/blue) and CMYK (cyan/magenta/yellow/black). RGB is generally used with on-screen graphics, whereas CMYK is used for printing purposes.

All color figures should be generated in RGB or CMYK color space. Grayscale images should be submitted in Grayscale color space. Line art may be provided in grayscale OR bitmap colorspace. Note that "bitmap colorspace" and "bitmap file format" are not the same thing. When bitmap color space is selected, .TIF/.TIFF/.PNG are the recommended file formats.

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When preparing your graphics IEEE suggests that you use of one of the following Open Type fonts: Times New Roman, Helvetica, Arial, Cambria, and Symbol. If you are supplying EPS, PS, or PDF files all fonts must be embedded. Some fonts may only be native to your operating system; without the fonts embedded, parts of the graphic may be distorted or missing.

A safe option when finalizing your figures is to strip out the fonts before you save the files, creating "outline" type. This converts fonts to artwork what will appear uniformly on any screen.

## V. EXPERIMENTS

### A. EXPERIMENTAL ENVIRONMENT

Our experimental system consists of a UWB(ultra wideband) sensor tag and eight anchors that have a UWB transceiver, the motion capture system with 12 cameras, a mobile robot and a small form-factor computer.

UWB sensor anchors are attached to landmarks. These become the end points of the range measurements. The anchor nodes transmit the UWB signal. A UWB sensor tag is attached to a robot. It becomes the opposite side end point of the measurements. The tag node receives the signal and measures the range between two devices. Each UWB transceiver, DW1000 UWB-chip made by Decawave, supports 6 RF bands from 3.5 GHz to 6.5 GHz. It measures in centimeter-level accuracy. Fig. 1(a) shows anchor and tag nodes.

We inference the position of a robot with our network. To train the network and test the results, the ground truths are needed. We get the ground truth by using the motion capture system. The system is Eagle Digital Realtime system of motion analysis corporation that operates with the principle of stereo pattern recognition that is a kind of photogrammetry based on the epipolar geometry and the triangulation methodology. We attach four markers to a robot. The system gives us the location of these markers and has $< 1$mm accuracy.

A mobile robot used in experiment is iClebo Kobuki from Yujinrobot that has 70 cm/s maximum velocity.The small form-factor computer is a gigabyte Ultra compact PC. Deep learning framework used for our network is pytorch 0.4.0 on python 3.6. The network inferences on the same setting.

The UWB tag is attached to mobile robot that has a small compact computer. The UWB anchors are attached to stands that have two different heights. The anchors are positioned randomly in the square space. As you can see in Fig. 1(b), a mobile robot manually goes on various random trajectories by experimenters.

During the robot is going on, the data is saved in the computer. The distance data used for input data is measured by the UWB sensors. The global position data used for ground truth is measured by the motion capture system. These two kinds of data are paired in a dataset. The computer receives these two kinds of data respectively and syncronizes these by time. To synchronize, we make an independent thread that concatenates and saves these data at the same time. The data is saved at 20Hz frequency. Each trajectory becomes one dataset. All the trajectories are different. Fig. 1(c) shows this process. After collecting whole datasets, we separate the entire dataset to two types, some are the training datasets and others are test datasets.

#### 1) Figure Axis labels

Figure axis labels are often a source of confusion. Use words rather than symbols. As an example, write the quantity "Magnetization," or "Magnetization M," not just "M." Put units in parentheses. Do not label axes only with units. As in Fig. 1, for example, write "Magnetization (A/m)" or "Magnetization ($A{\cdot}m^{-1}$)," not just "A/m." Do not label axes with a ratio of quantities and units. For example, write "Temperature (K)," not "Temperature/K."

Multipliers can be especially confusing. Write "Magnetization (kA/m)" or "Magnetization ($10^3$ A/m)." Do not write "Magnetization (A/m) $\times$ 1000" because the reader would not know whether the top axis label in Fig. 1 meant 16000 A/m or 0.016 A/m. Figure labels should be legible, approximately 8 to 10 point type.

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Multipart figures should be combined and labeled before final submission. Labels should appear centered below each subfigure in 8 point Times New Roman font in the format of (a) (b) (c).

### B. FILE NAMING

Figures (line artwork or photographs) should be named starting with the first 5 letters of the author's last name. The next characters in the filename should be the number that represents the sequential location of this image in your article. For example, in author "Anderson's" paper, the first three figures would be named ander1.tif, ander2.tif, and ander3.ps.

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If two authors or more have the same last name, their first initial(s) can be substituted for the fifth, fourth, third... letters of their surname until the degree where there is differentiation. For example, two authors Michael and Monica Oppenheimer's photos would be named oppmi.tif, and oppmo.eps.

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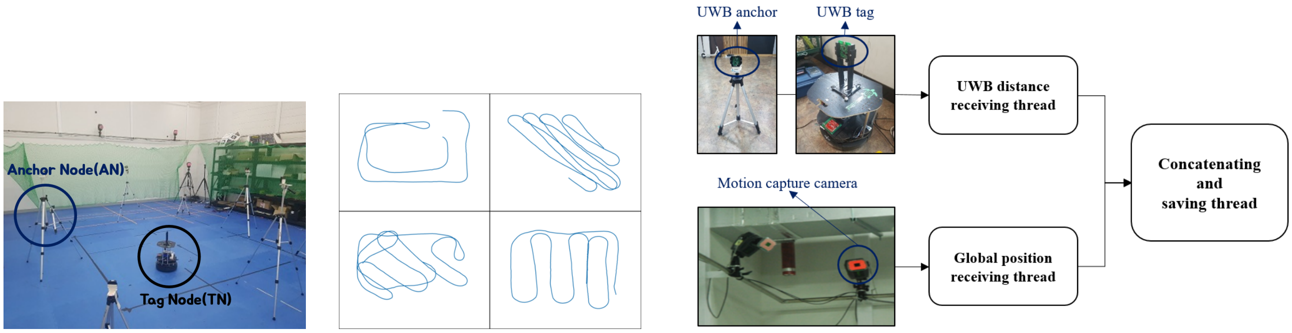
When referencing your figures and tables within your paper, use the abbreviation "Fig." even at the beginning of a sen-




(a) (b) (c)

FIGURE 1: Figures from experiment (a)The anchor and tag nodes (b)Four examples of the trajectory (c) the process that makes dataset

tence. Do not abbreviate "Table." Tables should be numbered with Roman Numerals.

### D. CHECKING YOUR FIGURES: THE IEEE GRAPHICS ANALYZER

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## VI. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

.

Appendixes, if needed, appear before the acknowledgment.

## ACKNOWLEDGMENT

The preferred spelling of the word "acknowledgment" in American English is without an "e" after the "g." Use the singular heading even if you have many acknowledgments. Avoid expressions such as "One of us (S.B.A.) would like to thank . . . ." Instead, write "F. A. Author thanks . . . ." In most cases, sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page, not here.

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References need not be cited in text. When they are, they appear on the line, in square brackets, inside the punctuation. Multiple references are each numbered with separate brackets. When citing a section in a book, please give the relevant page numbers. In text, refer simply to the reference number. Do not use "Ref." or "reference" except at the beginning of a sentence: "Reference [?] shows . . . ." Please do not use automatic endnotes in Word, rather, type the reference list at the end of the paper using the "References" style.

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[1]It is recommended that footnotes be avoided (except for the unnumbered footnote with the receipt date on the first page). Instead, try to integrate the footnote information into the text.

## APPENDIX A SUBMITTING YOUR PAPER FOR REVIEW

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