Tesla Blocks: Magnetism-Based Tangible 3D Modeling System using Block-Shaped Objects

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ABSTRACT

We herein demonstrate Tesla Blocks, a magnetism-based tangible 3D modeling system using block-shaped objects. The system recognizes the structure assembled by the user and draws the 3D model in real time. Each block of the system has a simple structure; we embed only a permanent magnet in a block. Because the electronic circuit used for recognizing the structure exists outside the blocks, the system is simple. Furthermore, occlusion by the user's hand does not occur in recognizing the structure.

CCS CONCEPTS

• **Human-centered computing → Graphics input devices**; *Interface design prototyping*; • **Hardware →** *Emerging interfaces*;

KEYWORDS

Tangible User Interface, building block, 3D modeling

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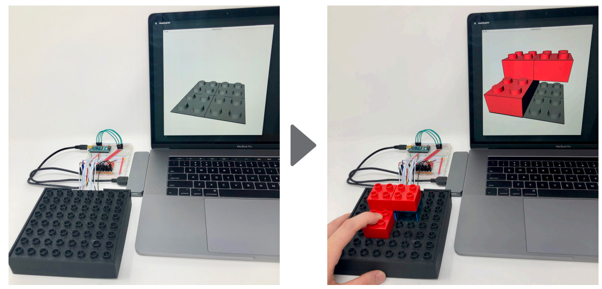

Figure 1: Tesla Blocks. When the user places the blocks on the hardware, the 3D model is drawn in real time.

1 INTRODUCTION

Many systems for tangible 3D modeling using block-shaped objects have been researched (e.g., [2–4, 21]); they recognize the assembled block structure (hereinafter block structure) and draw the 3D model. One outstanding merit of such 3D modeling is its tangible user interface (TUI). A TUI is designed to allow a user to manipulate intangible computer information by manipulating tangible objects in the real world directly(e.g., [9, 16, 22]). This design causes the objects perceived by the user and the objects manipulated by the user to be the same. By contrast, in graphical user interfaces (GUIs), the objects perceived by the user and those manipulated by the user are different. For example, the user perceives the cursor while manipulating a mouse in a desktop environment. Meanwhile, in tangible 3D modeling using block-shaped objects, the construction of a block structure is assembling block-shaped objects, where the objects perceived by the user and the objects manipulated by the user are the same. Therefore, using this manipulation as the input to the computer, 3D modeling using block-shaped objects could realize an easy-to-understand 3D modeling even for a user who is not familiar with computers.

To realize such a block-shaped TUI, it is necessary to recognize the block structure consisting of blocks. Such existing methods can be categorized into two groups. The first group recognizes the structure using electronic circuits including a microcontroller embedded in a block. The second group uses cameras installed, where the entire structure can be observed. However, the first group is disadvantageous because a complicated circuit must be incorporated in each block. The second group exhibits the following problems: the system tends to be bulky owing to the use of cameras; occlusion occurs by the user's hand.

To solve these problems, we explore a magnetism-based approach as another simple approach to recognize a block structure, and develop a magnetism-based tangible 3D modeling system named Tesla Blocks (Figure 1). The system recognizes the structure assembled by the user and draws the 3D model in real time. Each block of the system has a simple structure; we embed only a permanent magnet in a block. Because the electronic circuit used for recognizing the structure exists outside the blocks (i.e., in the base plate on which the user assembles the blocks in our current implementation), the system can be compact. Furthermore, occlusion by the user's hand does not occur as magnetism is used to recognize the structure.

2 RELATED WORK

Many techniques for recognizing block structures, methods for 3D modeling, and interaction techniques using magnetism have been studied.

2.1 Block Structure Recognition Techniques

Many techniques use built-in electronic circuit blocks or camera images. In addition, some uses capacitance measurement.

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2.1.1 Techniques using Built-in Electronic Circuit Blocks. Many techniques recognize structures using an electronic circuit incorporated into a block; the circuit transmits and receives electric signals via a metal connector. In the studies by Anderson et al. [2], Watanabe et al. [24], and Leen et al. [17], the microcontrollers embedded in the blocks communicate with each other to recognize the structure. Ando et al. [3] proposed StackBlock, a block in which infrared (IR) LEDs and phototransistors are laid in a grid pattern on all its six faces. Their system estimates the contact area between blocks by emitting and receiving IR light. Hosoi et al. [12] designed a building block with a magnetic sensor, accelerometer, and Bluetooth module. In addition to the number of blocks stacked, the system recognizes how each block is placed (blocks' direction and how blocks are aligned) in real time. In contrast to the studies above, our system realizes a block-shaped TUI with a simple structure by embedding a permanent magnet in each block.

Glauser et al. [10] and Wang et al. [23] built an object with joints that can bend and twist, with a microcontroller and sensor in the joint. The user can manipulate a 3D model by manipulating the joints of the structure assembled by these objects. Leen et al. [17] proposed StrutModeling that enables users without a 3D modeling background to prototype 3D models by assembling struts in a physical space. While it may become cheaper and easier to manufacture tangible blocks with integrated electronics in the future, our block would still be easier to be manufactured because it has a fairly simpler structure.

2.1.2 Techniques using Camera Images. Another approach uses cameras installed where the entire structure can be observed. The system of Baudisch et al. [4] uses a block composed of glass fiber and a marker. The system monitors the structure assembled by blocks with the camera under the desk, and recognizes the height of stacked blocks from the difference in the appearance of the marker from the bottom. The systems of Miller et al. [21] and Gupta et al. [11] recognize a structure using a depth camera. By contrast, our system is based on magnetism rather than cameras; therefore, it could realize a compact system compared to these systems and solves the misrecognition owing to occlusion.

2.1.3 Techniques by Capacitance Measurement. In addition to the two above approaches, another approach that uses capacitance measurement has been explored. Yoshida et al. [25] designed a block that is a capacitor formed by combining conductive and nonconductive filaments using a fused deposition modeling 3D printer. When these blocks are stacked, the capacitors are connected in parallel; therefore, the capacitance measured at the base increases linearly. The system detects the number of stacked blocks by mapping the measured capacitance with the number of blocks. In addition, Ikegawa et al. [15] created a tangible 3D modeling system that can recognize more number of blocks simultaneously using blocks with built-in capacitors. Chan et al. [7] developed a system that can detect the number of blocks stacked on a capacitive touch panel. When the user touches the side of the block when placing it, several touch points are generated that correspond to the number of blocks stacked on the touch panel. The system estimates the number of blocks from the combination of the generated touch points. Compared to the techniques described above, these techniques recognize the block structure without incorporating microcontrollers into blocks, and also solve the occlusion problem by detecting the capacitance of the blocks. Similarly, our method realizes the recognition of the structure by another simple method of embedding a permanent magnet in each block.

2.2 Magnetism-Based Interaction Techniques

Research on interaction techniques based on magnetism has also been conducted actively. Bianchi et al. [5, 6] embedded permanent magnets into a tangible tool that can be used in combination with a smartphone. By measuring magnetism with the built-in magnetic sensor, the smartphone detects where the tool was placed and determines how the tool was manipulated. uTrack by Chen et al. [8] uses two triaxial magnetic sensors to track the position and angle of permanent magnets. uTrack realizes real time 3D inputs using the thumb with one permanent magnet and the ring finger with two magnetometers. Abe et al. [1] proposed input techniques for smartphones using a stylus with a permanent magnet. Using these techniques, the user can use the surface on which the smartphone is placed as the surface for the stylus input. Huang et al. [13, 14] proposed IM6D, which is a real-time magnetic motion-tracking system. IM6D uses an array of pickup coils to track the position and orientation of each wireless LC coil. By contrast, we use permanent magnets and magnetic sensors to recognize the structure of the assembled blocks.

Similar to our system, some TUI studies that use permanent magnets and magnetic sensors also arrange the magnetic sensors in a grid pattern. Liang et al.'s GaussStones [20] is a system that uses markers with built-in permanent magnets inside a magnetic shield. Markers are recognized by measuring the locally generated magnetism using the magnetic sensor array (GaussSense [19]) on the back of the liquid crystal panel. This system can recognize up to two stacked markers. GaussBricks [18] uses the same hardware as GaussSense and recognizes the combination of bone-shaped parts, each of which contains two magnets attached to both ends. Meanwhile, we realize a tangible 3D modeling system using a block with a permanent magnet and a magnetic sensor array.

3 TESLA BLOCKS

Tesla Blocks is a system that recognizes the structure assembled by the user and draws the recognized structure as a 3D model in real time (Figure 1). The system consists of block-shaped objects (LEGO bricks), hardware with magnetic sensors array placed in a grid pattern (Magnetism Measurement Hardware), Structure Recognition Software, and 3D model viewer. By assembling the blocks, i.e., blocks containing a magnet (magnetic block, Figure 2, left) and blocks without magnets (empty block, Figure 2, right), the user can construct the block structures to exhibit pseudo hollows.

3.1 Magnetic Block

We created a magnetic block by embedding a permanent magnet inside a 2×2 LEGO Duplo block. A magnetic block consists of a LEGO Duplo block (Figure 3 left), fixture (Figure 3 middle), and permanent magnet (Figure 3 right). In our current implementation, we used a cylindrical neodymium magnet with a diameter of 6 mm, a height of 2.5 mm, and a magnetic flux density of 220 mT on the top/bottom base as the permanent magnet. Because the cavity inside the 2×2 LEGO Duplo block is a cylinder with a diameter of

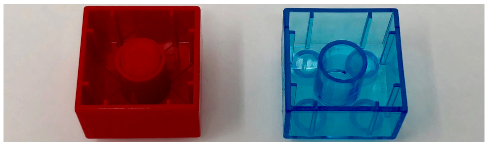

Figure 2: Block-shaped objects: left) magnetic block, and right) empty block.

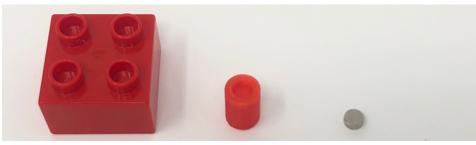

Figure 3: Components of a magnetic block: left) 2×2 LEGO Duplo, middle) fixture, right) neodymium magnet.

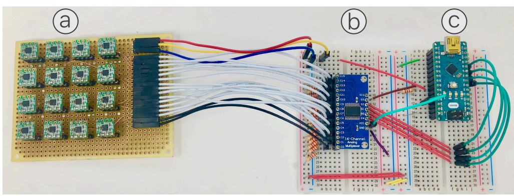

Figure 4: Components of Magnetism Measurement Hardware: a) triaxial magnetic sensors arranged into a grid of 4×4, b) 16-channel analog multiplexer, c) microcontroller.

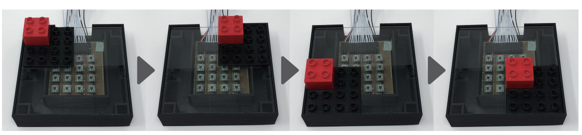

Figure 5: Moving a block structure in four places to acquire pseudo 64 magnetic sensor values.

10.8 mm, we used a cylinder-shaped fixture to fix the magnet in the cavity (Figure 2 left). The fixture has a cylindrical cavity on the top with a diameter 6.25 mm and a height of 2.5 mm to hold the magnet. We designed this fixture and printed it with a fused deposition modeling 3D printer.

3.2 Magnetism Measurement Hardware

Magnetism Measurement Hardware measures the magnetism of the block structure assembled by the users (Figure 4). It consists of 16 triaxial magnetic sensors (Figure 4a, Honeywell International Inc., HMC5883L), a 16-channel analog multiplexer (Figure 4b, CD74HC4067 by Texas Instruments), and a microcontroller (Figure 4c, Arduino Nano). We arranged the magnetic sensors into a 4×4 grid with the distance between the sensors of 15.24 mm on the universal board. To allow the user to assemble blocks above the magnetic sensors, we 3D-printed a case for the magnetic sensor array to be fitted to the hardware. This case is a rectangular parallelepiped of 135 mm in length and width and 31.5 mm in height. On the top of this case, 8×8 studs are placed similarly as the LEGO Duplo base plates, allowing the user to assemble blocks above the magnetic sensor array. We set up each magnetic sensor to measure the magnetism at 75 Hz with a detection range of ±0.56 mT and to send the average value of eight samples to the microcontroller. Because the slave address used for the I^2C communication of the magnetic sensor is fixed, we used a multiplexer for enabling communication between the microcontroller and multiple magnetic sensors.

3.3 Structure Recognition Software

Structure Recognition Software, implemented in Python 3.6.5, recognizes a block structure by using the fact that the magnetic fields of multiple magnets are additive. Namely, if a block structure is placed on a hardware, the magnetic field observed by each magnetic sensor is the sum of the magnetic fields at the sensor from the magnetic blocks constituting the structure.

Based on this fact, the software recognizes the structure by using the magnetic fields recorded by all the sensors (training data). Assume that the system accepts a block structure with a size of up to $w \times d \times h$ blocks; that is, the user can assemble $2^{w \times d \times h}$ patterns of block structures. Moreover, let $\vec{b}_{x,y,z}$ be the magnetic fields observed by the n triaxial magnetic sensors when a magnetic block is placed at (x, y, z):

$$\vec{b}_{x,y,z} = (b_{x,y,z,1}, \cdots, b_{x,y,z,3n}),$$

where $b_{x,y,z,i}$ $(i = 1, \cdots, 3n)$ are the magnetic field values sensed by the sensors.

To obtain the training data, first, we recorded the values of each sensor when no magnetic block was placed on the hardware. This is considered as the offset to eliminate the influence of geomagnetism and magnetism of surrounding electronic devices. Second, we recorded $\vec{b}_{1,1,1}, \cdots, \vec{b}_{w,d,h}$ by placing one magnetic block at one position from $(1, 1, 1)$ to (w, d, h) one by one. Finally, we created a matrix B from the $w \times d \times h$ vectors as the training data:

$$\mathbf{B} = \begin{pmatrix} \vec{b}^{\mathrm{T}}_{1,1,1} & \vec{b}^{\mathrm{T}}_{2,1,1} & \cdots & \vec{b}^{\mathrm{T}}_{w,d,h} \end{pmatrix}.$$

Let $\vec{s} = (s_{1,1,1}, \cdots, s_{w,d,h})$ be the vector that represents a block structure assembled by the user, where $s_{x,y,z} \in \{1, 0\}$ (1: a magnetic block is placed at (x, y, z); 0: otherwise). In this case, the magnetic fields $\vec{m} = (b_1, \cdots, b_{3n})$ observed by the n sensors will be:

$$\vec{m}^{\mathrm{T}} = B\vec{s}^{\mathrm{T}}.$$

Therefore, by measuring $\vec{m}$, we can estimate the block structure $\vec{s}$ as follows:

$$\vec{s}^{\mathrm{T}} = B^{-1}\vec{m}^{\mathrm{T}}, \tag{1}$$

where B^{-1} is the pseudo-inverse matrix of B. Note that the offsets must be measured again before measuring $\vec{m}$ when the hardware is moved while B remains reusable even when the hardware is moved.

However, since there are individual differences in sensors, permanent magnets, and attachment of permanent magnets and the observed magnetic fields contain noise, the components of the derived $\vec{s}$ with Equation 1 varie around 0 or around 1. Therefore, we use a threshold for estimation: if the component is greater than the threshold, the software estimates that there is a magnetic block at the corresponding position (0.5 in our current implementation).

3.4 3D Model Viewer

We implemented a 3D model viewer that recognizes the structure of the magnetic blocks assembled by the user and obtain the result as a 3D model. This application receives the results sent from Structure Recognition Software using OpenSound Control. We

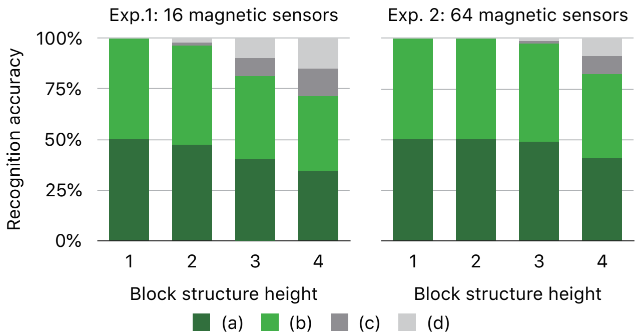

Figure 6: Block recognition accuracies of Exp. 1 and 2: a) a block existed as expected, b) no block existed as expected, c) a block existed unexpectedly, d) no block existed unexpectedly.

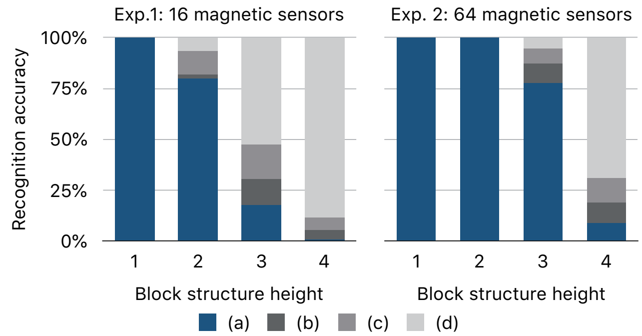

Figure 7: Structure recognition accuracies of Exp. 1 and 2: a) all blocks were correctly recognized, b) one or more blocks existed unexpectedly, c) fewer blocks existed unexpectedly, d) structures including both b and c.

implemented this viewer using Processing. We used P3D, which is the standard 3D drawing engine of Processing for drawing 3D models. The user can move the viewpoint and zoom the model using the mouse for an easier visualization of the 3D model.

4 EVALUATION

We conducted two experiments to examine the recognition accuracy of the Tesla Blocks.

4.1 Experiment

We conducted Experiment 1 (Exp. 1) with 16 magnetic sensors and Experiment 2 (Exp. 2) with 64 pseudo-magnetic sensors. In both experiments, we attempted to recognize the block structures with the size of up to 2×2×h (h = 1. . .4).

4.1.1 Exp. 1. As a setup, we prepared four files containing the magnetic values required to recognize a structure with the size of up to 2×2×4. First, we selected one file and created a matrix **B** from the file. Second, we selected another from the remaining three files to calculate the magnetic values of all block structure patterns ($2^{2\times2\times h}$ patterns) from the file. Finally, we calculated the recognition accuracy using the magnetic values of all structure patterns. In this study, we calculated two types of recognition accuracy. The first one is the recognition accuracy in which each block of the block structure is recognized correctly (block recognition accuracy). The second one is the recognition accuracy in which the entire block structure is correctly recognized (structure recognition accuracy). We repeated the process above to obtain the average and standard deviation of the two recognition accuracies for all combinations (i.e., 4×3 combinations) of the four files.

4.1.2 Exp. 2. In addition, we hypothesized that recognition accuracy would be improved by increasing the number of magnetic sensors. To examine this, we increased the number of magnetic sensors virtually to 64 by moving the block structure in four places, as shown in Figure 5. With this setting, we obtained the two recognition accuracies with the same method as Exp. 1.

4.2 Results

We demonstrate the block recognition accuracy of Exp. 1 and 2 in Figure 6. Figure 6a–b show the percentage of correct recognition, and 6c–d show that of incorrect recognition. The block recognition accuracy of block structures with the size of up to 2×2×4 was 71% (SD = 0.035, Figure 6 left). Moreover, this result shows that increasing the number of magnetic sensors improves the accuracy to 82% (SD = 0.031, Figure 6 right).

We demonstrate the structure recognition accuracy of Exp. 1 and 2 in Figure 7. Figure 7a shows the percentage of correct recognition and 7b–d show that of the incorrect recognition. The recognition accuracies of the block structures with the size of up to 2×2×3 and 2×2×4 were 18% (SD = 0.134) and 0.8% (SD = 0.008), respectively (Figure 7 left). By contrast, by increasing the number of magnetic sensors, the accuracies were improved to 77% (SD = 0.198) and 8.8% (SD = 0.040), respectively (Figure 7 right). In addition, by increasing the block structure height, the proportion in incorrect accuracy Figure 7d is improved.

5 SUMMARY AND FUTURE WORK

In the evaluation, we discovered that recognition accuracy was improved by increasing the number of magnetic sensors. To apply this finding, we plan to implement a hardware with increased number of magnetic sensors, and attempt the real time recognition of larger block structures. Conversely, we found that the number of sensors could be increased by moving the structure or the magnetic sensor; thus, we will consider minimizing the number of sensors.

In this system, if a user placed a block at the coordinates not recorded beforehand, the system would misrecognize (for example, a structure in which the block is shifted by half). Although the current system could not recognize the structure above, we perceive that the system can be recognized by devising the data to be recorded in advance.

In this study, we demonstrated a magnetism-based tangible 3D modeling system that used block-shaped objects, which we call Tesla Blocks. Our system used a block with a simple structure that contained a permanent magnet. Our system recognized the block structure based on magnetic measurements and presented the recognition result as a 3D model in the display. The experiments indicated that increasing the number of magnetic sensors improved the recognition accuracy of Tesla Blocks.

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