A Block System with Magnetism-based Structure Recognition

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Abstract
We present a block system with magnetism-based structure recognition. The system allows users to create 3D models intuitively by assembling physical blocks, each of which has a simple structure with a permanent magnet. The system recognizes the structure of assembled blocks by using hardware with Hall sensors array.

Author Keywords
Tangible User Interface; TUI; building block; 3D modeling; computational device; interactive device.

ACM Classification Keywords
H.5.2 [Information Interfaces and Presentation (e.g. HCI)]: User Interfaces - Input devices and strategies.

Introduction
A tangible user interface (TUI) has been proposed that allows intangible computer information to be manipulated by direct manipulation on tangible objects in real world (e.g., [7, 10, 15]). As one of such TUIs, block-shaped TUIs (e.g., [1, 3, 14]) have been studied, which enable 3D modeling by assembling tangible blocks such as LEGO[1]. Compared to traditional 3D modeling using a mouse and keyboard, 3D modeling by assembling tangible blocks is intuitive because the formed 3D model and structure are synchronized in real

[1] https://www.lego.com

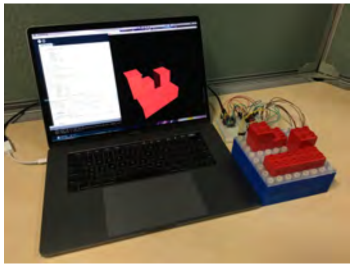

Figure 1: Overview of our system named Tesla Blocks.

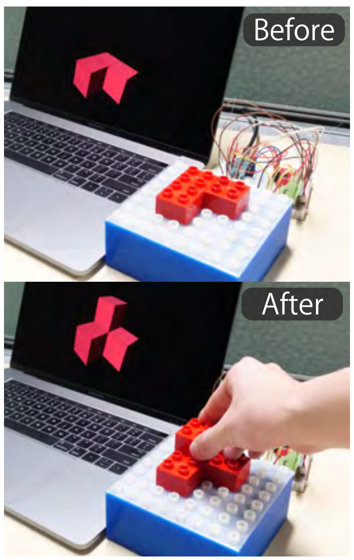

Figure 2: Operation example of Tesla Blocks: (upper) before adding a block, (lower) after adding a block.

time. Therefore, a block-shaped TUI has the possibility to realize 3D modeling for beginners and children.

To realize such a block-shaped TUI, it is necessary to recognize the structure of the assembled blocks. Such methods can be categorized into two groups. The first ones recognize the structure by electronic circuits including a built-in microcontroller in the block. The second ones use cameras installed where the entire structure can be observed. However, the first ones have a disadvantage that it is necessary to incorporate a complicated circuit in each block. The second ones suffer from problems: the system tends to be bulky due to the use of cameras; occlusion occurs by the hand of the user.

To solve these problems, we are exploring a magnetism-based approach as another approach to recognize the structure of assembled blocks, and developed a block structure recognition system named Tesla Blocks (Figure 1). Figure 2 shows the opertion example of the system. The system recognizes the structure assembled by the user and draws the 3D model. Each block of the system has a simple structure, in which we embed only a permanent magnet. Since the electronic circuit used for recognizing the structure exists outside 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 users' hand does not occur since magnetism is used to recognize the structure.

In this paper, as the first step to explore our magnetism-based approach to recognize the structure of assembled blocks, we report our small-scale implementation of the system and discuss how to scale up the system in future.

Related Work

Many methods to recognize the structure of the assembled blocks have been investigated in block-shaped TUIs studies.

One representative method uses electronic circuits, including a built-in microcontroller in the block. In the studies by Anderson et al. [1] and Watanabe et al. [16], the microcontrollers embedded in the blocks communicate with each other to recognize the structure when the user assembles blocks. Ando et al. [2] proposed StackBlock, which is 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. Structure recognition is realized by transferring data between blocks with IR communication. Hosoi et al. [9] designed a building block with a Hall 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 above studies, our system realizes a block-shaped TUI with simple structure by embedding a permanent magnet in each block. While it may become cheaper and easier to manufacture tangible blocks with integrated electronics in the future, our block would be still easier to be manufactured because it has a fairly simpler structure.

Another representative method uses cameras installed where the entire structure can be observed. The system of Baudisch et al. [3] 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 of how the bottom of the marker looks. The system of Miller et al. [14] and Gupta et al. [8] recognize the structure of blocks by 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 due to occlusion.

In addition to the above two representative methods, some other methods have been explored. Yoshida et al. [17] designed a block, which 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. Chan et al. [6] developed a system that can detect the number of blocks stacked on a capacitive touch panel. Each block has four or more contact points on its top and bottom. When the user touches the side of the block when placing it, several touch points are generated which 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 methods described above, these methods recognize the structure of the assembled blocks without incorporating microcontrollers into blocks, and also solves the occlusion problem by detecting the capacitance of blocks. Our method realizes recognition of the structure by a new method of embedding a permanent magnet in each block.

Research on TUIs based on permanent magnets and Hall sensors has also been actively conducted. Bianchi et al. created a tangible tool that can be used in combination with smartphones with built-in Hall sensors, by using three types of permanent magnets [4]. Each tool such as a slider and dial has one or more permanent magnets inside. By measuring magnetism, the system detects where the tool was placed around the smartphone or how the tool was used, which extends interaction of a smartphone. Furthermore, Bianchi et al. proposed a marker with a battery, motor, and magnet [5]. The magnet is embedded in the tip of the motor, and the rotation speed of each motor is uniquely adjusted. As the permanent magnet of the marker rotates, the polarity of SN changes. The system distinguishes the type of the marker by analyzing the frequency, and applies it to various applications. By contrast, we use permanent magnets and Hall sensors to recognize the structure of the assembled blocks.

Similar to our system, some research of TUIs using permanent magnets and Hall sensors also arrange the Hall sensors in a grid pattern. Liang et al. ’ s GaussStones [13] 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 Hall sensor array (GaussSense [12]) on the back of the liquid crystal panel. This system can recognize up to two markers stacked. GaussBricks [11] uses the same hardware as GaussSense and recognizes the combination of bone-shaped parts with magnets attached to the both ends. From this, it realizes various interaction on the touch panel. On the other hand, we realize a block-shaped TUI by using permanent magnets and Hall sensors.

Tesla Blocks

Tesla Blocks is a system that recognizes the structure assembled by the user and draws the recognized structure as a 3D model (Figure 1). Tesla Blocks is composed of blocks each of which contains a permanent magnet (*magnetic block*), hardware with Hall sensors array placed in a grid pattern (Structure Recognition Hardware), and 3D Model Viewer. In this section, we will describe the components and method of structure recognition based on

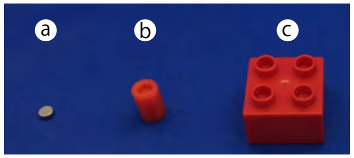

Figure 3: Components of the magnetic block: (a) permanent magnet, (b) spacer, (c) 2×2 LEGO duplo.

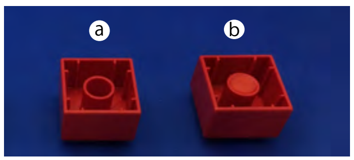

Figure 4: The cylindrical cavity inside the 2×2 LEGO duplo: (a) cavity, (b) cavity with a spacer inserted.

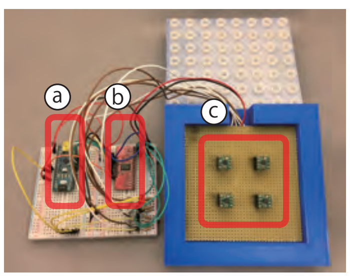

Figure 5: Appearance of the structure recognition hardware: (a) arduino Nano, (b) multiplexer, (c) four three-axis Hall sensors.

magnetism in Tesla Blocks.

Magnetic Block

We created a magnetic block by embedding a permanent magnet inside a 2×2 LEGO duplo. Figure 3 shows the components of the magnetic block. The magnetic block consists of a permanent magnet (Figure 3a), spacer (Figure 3b), and LEGO duplo (Figure 3c). In our current implementation, we use a neodymium magnet with a diameter of $6\,\mathrm{mm}$, a height of $2.5\,\mathrm{mm}$, and magnetic flux density of $220\,\mathrm{mT}$ on the surface as the permanent magnet. The cylindrical cavity inside the 2×2 LEGO duplo has a diameter of $10.8\,\mathrm{mm}$ (Figure 4a). Therefore, we used a spacer to fix the permanent magnet in the cavity (Figure 4b). The spacer is cylinder with a diameter of $10.5\,\mathrm{mm}$ and a height of $16.0\,\mathrm{mm}$. The spacer has a cavity on the top with a diameter $6.25\,\mathrm{mm}$ and a height of $2.5\,\mathrm{mm}$ to fix the permanent magnet. We designed this spacer and printed it with a fused deposition modeling 3D printer.

Structure Recognition Hardware

We implemented hardware for recognizing the structure of the magnetic block assembled by the user (Figure 5). The hardware is composed of a microcomputer (Figure 5a, Arduino Nano), a 16 channel analog multiplexer (Figure 5b, CD74HC4067 by Texas Instruments), and four three-axis Hall sensors (Figure 5c, HMC5883L by Honeywell). We mounted the Hall sensors on the universal board as a grid of 2×2 with $32\,\mathrm{mm}$ between each sensor. To allow the user to assemble magnetic blocks above the Hall sensors, we 3D-printed a case for the Hall sensor array to be fitted to the hardware. This case is a rectangular parallelepiped of $128\,\mathrm{mm}$ in length and width and $50\,\mathrm{mm}$ in height. On the top of this case, 8×8 projections are placed in the same way as LEGO duplo, allowing the user to assemble blocks above the Hall sensor array. Each Hall sensor sends measured values to the microcomputer at $75\,\mathrm{Hz}$. We setup the sensor to have a detection range of $\pm 0.47\,\mathrm{mT}$. Since the slave address used for $\mathrm{I^2C}$ communication of the Hall sensor was fixed, we used a multiplexer for enabling communication between the microcomputer and multiple Hall sensors.

3D Model Viewer

We implemented a 3D model viewer that recognizes the structure of the magnetic blocks assembled by the user and draws the result as a 3D model. Figure 6 shows a screenshot of the 3D model viewer. We 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 to make it easy to see the 3D model.

Block Recognition Method

Tesla Blocks recognizes the structure by comparing the measured values with Structure Recognition Hardware to the predicted values of every structure created from training data beforehand, and draws the 3D model of the structure with the closed predicted values. In this section, we show how to create the training data and how to recognize the structure using the training data.

Creating Training Data

Firstly, assume that the user can stack blocks on each coordinate of a $N \times N$ grid. Now, a 3D structure can be represented as a $N \times N$ two-dimensional array, since 0 or more blocks can be stacked for each coordinate of the $N \times N$ grid. To create training data, we recorded measured values of the Hall sensors by changing the number of blocks stacked from 1 to M. We did this to each coordinate of the $N \times N$. That is, we recorded $N \times N \times M$ patterns of

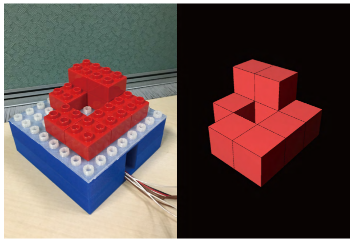

Figure 6: Screenshot of our 3D model viewer: (left) structure assembled by the user, (right) the 3D model drawn by the 3D Model Viewer.

measured value as the training data. In order to eliminate the effect of the geomagnetism, we also used the sensor value when the magnetic block was not placed on the Structure Recognition Hardware as an offset.

Recognition Algorithm

We use the fact that the additive theorem can be applied to magnetic vectors. That is, if a certain structure is given, the measured values of the Hall sensors must be the sum of some training data.

We currently assume that a block is added/removed one by one by the user (in order to reduce the search cost). In addition, we also assume that there is no block stacked when the system starts.

The recognition of the structure begins with calculating sensor values of possible structures (predicted values), assuming that one block is added to or removed from the current structure (this calculation is performed when the user presses the Enter key). For example, Table 1 shows all the possible structures when $N = 2$ and the current structure has a height of $\{a_x | x = (0,0) \cdots (1,1)\}$. The system does this calculation by adding a training datum to the current measured value or subtracting a training datum from the current measured value. Then, the system compares the predicted values with the current measured values. The structure with the closest predicted sensor values to the measured value is used as the search result, and the 3D model is drawn on the viewer.

Experiment

We investigated the size of the structure which can be recognized by Tesla Blocks. Firstly, we investigated the height of the structure that the system can recognize correctly when the bottom of the structure was 2×2. To do this, we first created training data of measured values of

Table 1: Possible structures with 2×2 data sets.

	Code of estimated structure			
No change	$a_{(0,0)}$	$a_{(0,1)}$	$a_{(1,0)}$	$a_{(1,1)}$
Remove a block	$a_{(0,0)} - 1$	$a_{(0,1)}$	$a_{(1,0)}$	$a_{(1,1)}$
	$a_{(0,0)}$	$a_{(0,1)} - 1$	$a_{(1,0)}$	$a_{(1,1)}$
	$a_{(0,0)}$	$a_{(0,1)}$	$a_{(1,0)} - 1$	$a_{(1,1)}$
	$a_{(0,0)}$	$a_{(0,1)}$	$a_{(1,0)}$	$a_{(1,1)} - 1$
Add a block	$a_{(0,0)} + 1$	$a_{(0,1)}$	$a_{(1,0)}$	$a_{(1,1)}$
	$a_{(0,0)}$	$a_{(0,1)} + 1$	$a_{(1,0)}$	$a_{(1,1)}$
	$a_{(0,0)}$	$a_{(0,1)}$	$a_{(1,0)} + 1$	$a_{(1,1)}$
	$a_{(0,0)}$	$a_{(0,1)}$	$a_{(1,0)}$	$a_{(1,1)} + 1$

$2 \times 2 \times 1$ pattern. After giving the training data to the system, we freely created structures with 2×2 and a height of 1 or less. As a result, we observed that the system could recognize all the structures correctly. After that, we created a new set of training data by increasing the height of the block by 1, gave it to the system, and repeated the investigation. As a result, we observed that the system recognized the structure with a height of 3 correctly; however the structure with a height of 4 had recognition errors. Next, we investigated the height of the structure that the system could recognize correctly when the bottom of the structure was 3×3. As a result, the system recognized the structure with a height of 2 correctly; however the structure with a height of 3 had recognition errors.

Discussion and Future Work

One reason for the false recognition might be the magnetic field characteristics. As the structure becomes higher, the distance between the position where the block is newly placed and the Hall sensor increases. Since the magnetism is attenuated in inverse proportion to the square of the distance, the increase of the sensor value by the newly placed block becomes smaller and thus the recognition accuracy lowers. In addition, we assume that the magnetic block error (e.g., permanent magnet magnetism and spacer size) and Hall sensors ’ accuracy might be another reason. Therefore, we plan to improve the accuracy, by increasing the number and density of Hall sensors. In contrast to our current system where four Hall sensors are arranged in a 2×2 grid pattern, we will investigate how increasing the number of Hall sensors (e.g., using nine Hall sensors in a 3×3 grid pattern) affects the accuracy. Moreover, we will investigate various arrangements of the Hall sensors to solve the problem due to magnetic field characteristic to improve the accuracy (e.g., three-dimensional arrangement).

In addtion to the accuracy, another issue is the scalability in training. Currently, it is necessary to create training data according to the size of the structure in advance; the training efforts increase quadratically with the area and the height of construction. To address this issue, we plan to incorporate an algorithm to track the 3D position of magnets to remove the requirement for training data. One example will be the algorithm adopted in uTrack [7], which uses two three-axis Hall sensors to detect the position (and rotation) of the magnet attached to the fingertip. Moreover, this incorporation could solve another limitation where the user has to press a key to activate the recognition in order to reduce calculation cost in our current implementation, because searching the predicted data become totally unnecessary by using such tracking algorithm.

Still, our system has the following limitations. While our system solves the occlusion problem occurred by the hand of the user, the may not operate correctly when there is a magnetic material or magnetic shield near the system and they move dynamically. Moreover, in order to eliminate the effect of geomagnetism, the system records offsets at startup; therefore, when Structure Recognition Hardware is moved while the system is used, it is necessary to reset the offset explicitly. Therefore, some dynamic calibration technique should be incorporated.

Conclusions

We showed a magnetism-based approach as another approach to recognize the structure of assembled blocks. Each block has a simple structure with a permanent magnet. The structure of the assembled blocks is recognized by using a hardware with a Hall sensor array. We also showed the design and implementation of a prototype system called Tesla Blocks. In our system, the electronic circuit used to recognize the structure is integrated into the base plate on which the user assembles the structure. Therefore, our system realized a compact system compared with systems using a camera. Our current implementation could recognize the structure with the bottom of 2×2 of a height up to 3 correctly; it also could recognize the structure with the bottom of 3×3 of a height up to 2 correctly. In the future, we plan to pursue the cause of recognition errors and try to improve the system.

Future Impact

Block-shaped TUIs allow users to create 3D models intuitively by assembling physical blocks. Therefore, they can be used even by beginners and children. Nowadays, fabrication tools such as 3D printers can now be introduced easily to homes casually. We believe that, in combination of such fabrication tools, 3D modeling tools based on our approach will promote fabrication and manufacturing by general users to daily activities in the future.

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