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3.4
Sensing Chair and Floor Using Distributed Contact Sensors

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3.4.1
Introduction

As computing becomes more ubiquitous and distributed, there is a growing need for the computing environment to become more aware of the people present and activities that take place around it. In a futuristic intelligent office building, every piece of furniture and building structure becomes a perceptual user interface – it sees, hears, and feels its surrounding as well as the people around it. This can be accomplished by providing objects with sensory mechanisms similar to our own – camera for vision, microphone for hearing, and pressure sensors for touch. Numerous systems have been developed that explore the idea of perceptual intelligence [1–8]. Among these, very few employ touch-based sensory information. Our Sensing Chair and Sensing Floor projects are conceptualized to explore the use of *distributed* pressure information, from sensors that are analogous to artificial skin, to achieve perceptual intelligence.

Perceptual intelligence for a building cannot be achieved by merely collecting and displaying sensory information, such as most webcams do. Perceptual intelligence results from an understanding of what the sensory data reveal about the state of the environment and people. The key research problem to be addressed with the Sensing Chair and Sensing Floor, therefore, is the automatic processing and interpretation of touch sensor information, and the modeling of user behavior leading to such sensory data. We envision tomorrow's buildings where all objects are outfitted with a layer of artificial skin (for example, a sensing chair, a sensing floor, a sensing file folder). We expect the algorithms and behavior models that we develop with the Sensing Chair and Sensing Floor to be extensible to large-scale distributed haptic (touch-based) sensing and interpretation.

To enable a chair to sense and interpret its occupant's actions, pressure distribution sensors are surface-mounted on the seatpan and backrest of a Sensing Chair. Work on the Sensing Chair draws upon current advances in computer vision, pattern recognition and stochastic modeling, taking advantage of the similarity between pressure-distribution maps and gray-level images. To enable a floor to sense and estimate the positions of its occupants, force-sensing resistors are placed under the corners of floor panels that make up a suspended floor structure. The sensor readings are then combined and compared with a threshold to determine whether the floor panel is occupied.

The successful implementation of a Sensing Chair and a Sensing Floor will impact many areas including ergonomics (by monitoring a person's sitting posture and giving feedback when necessary), multimodal human-computer interface research (by providing new haptic systems that can be integrated with other state-of-the-art user interfaces for multimodal interaction), intelligent environment (by creating interfaces that can feel their environment with contact sensors), universal access (by empowering people with limited sensory and motor capabilities with assistive interfaces), and safety of automobile operation (by augmenting a driver's seat with sensors that can automatically regulate airbag deployment force).

3.4.2
Related Work

Many systems have been developed around the structure of a chair. The British Telecom SmartSpace, for example, is a concept personal working environment of the future, built around a swivel chair (http://www.bt.com/innovation/exhibition/smartspace/index.htm). It is equipped with a horizontal LCD touchscreen, video projection, and 3D sound space. In contrast, the goal of our Sensing Chair is to achieve information extraction by instrumenting the chair itself.

BCAM International (Melville, NY, USA) has developed a recliner with pneumatically controlled air bladders placed near the surface of the recliner that can be inflated to 'hug' and support the occupant's body. This technology, called the 'intelligent surface', has recently been implemented in United Airline's Connoisseur Class seats [9, 10]. It should be pointed out that the air bladder activation patterns are based on ergonomic considerations, rather than on the needs of its occupant. The Sensing Chair can provide the needed intelligence to such mechanisms so that surface distribution can be altered in response to the real-time pressure distributions in the chair in an ergonomically beneficial manner.

Pressure distribution sensors have been widely used for the evaluation of weight-supporting surfaces in shoes, chairs, and beds. Examples of shoe studies include the assessment of seven types of shoes with regard to their ability to reduce peak pressure during walking for leprosy patients [11], the evaluation of the generalizability of in-shoe peak pressure measures with data collected from numerous subjects over a period of time using two calibration schemes [12], and the validation of the use of total contact casts for healing plantar neuropathic ulcerations through reduction of pressure over the ulcer [13]. Studies of seats include the development of a measurement protocol and analysis technique for assessing pressure distribution in office chairs [14], the use of body pressure distribution measures as part of a series of tests for assessing comfort associated with five automobile seats [15], and an interesting review of how objective pressure measures can lead to improved aircrew seating with more evenly distributed pressure patterns, thereby potentially improving a pilot's task performance by reducing or eliminating pain endured during high-acceleration maneuvers of the aircraft [16]. Examples of bed studies include an investigation of support surface pressure and reactive hyperemia (the physiological response to pressure) in the older population [17], and a recent development of body posture estimation system for sleepers based on pressure distribution measures and a human skeletal model [18].

Our Sensing Chair and Sensing Floor projects are similar to the last study cited [18] in that we focus on the automatic processing and interpretation of contact sensor information, whereas the other studies rely on expert analysis of pressure distribution measures. Of particular importance is the development of real-time systems that can be used to drive other processes such as a sitting posture monitoring system for persons with chronic lower-back pain, or for the prevention of such ailments.

3.4.3 The Sensing Chair System

3.4.3.1 Overview

The long-term goal of the Sensing Chair project is to model the sitting postures of the person occupying the Sensing Chair (Figure 3.4-1). As shown in Figure 3.4-2, the Sensing Chair project is further divided into the two components of Static Posture Classification (identification of steady-state sitting postures), and Dynamic Posture Tracking (continuous tracking of steady-state as well as transitional sitting postures). In each case, we start with a single-user system and proceed to a multi-user system. Our ultimate aim is a robust, real-time, and user-independent sitting posture tracking system.

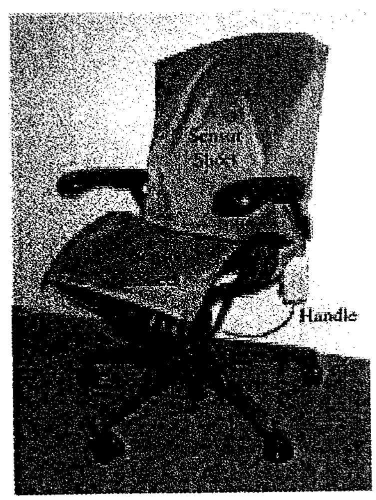

Fig. 3.4-1 The sensing chair

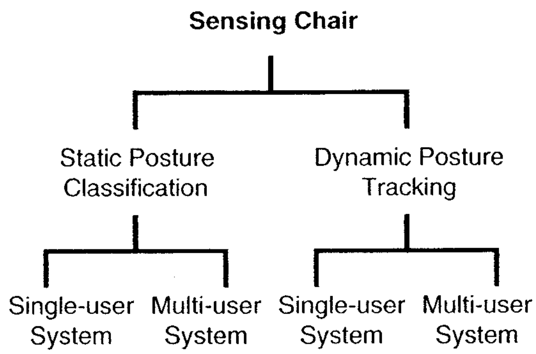

Fig. 3.4-2 Overview of the sensing chair project

Given the similarity between a pressure map and an 8-bit gray-scale image (see Figure 3.4-3), it is speculated that pattern recognition algorithms developed for computer vision would be applicable to the interpretation of sitting postures from pressure distribution data. There are two major approaches to object representation and recognition in computer vision: model-based (eg, [19]) and appearance-based (eg, [20]). The latter is considered more applicable since the concept of object model does not apply directly to pressure maps. Appearance-based modeling and object recognition involves the two steps of training and recognition. First, a set of training images is obtained. The technique of principal components analysis (PCA, also known as 'eigenspace methods', 'eigen-decomposition', or 'Karhu-

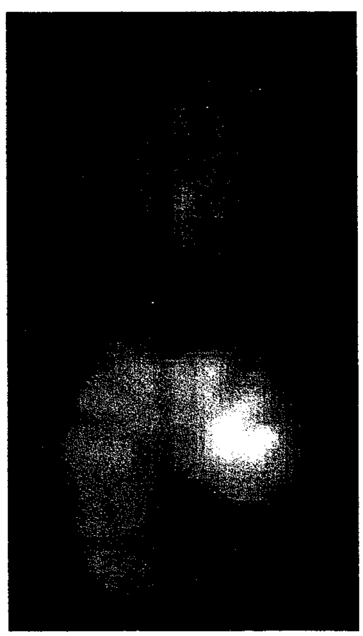

Fig. 3.4-3 A full pressure map for the posture 'left leg crossed'. See text for details

nen-Loeve expansion') [21] is often applied to the training data to obtain a low-dimensional representation (eigenspace) for the training and test images. Recognition of a test object is performed by projecting a test image on to the eigenspace and comparing the distance between the test image and image models derived from training. This is the approach that we have taken for static posture classification. Our work is based primarily on the computer face recognition work conducted at the MIT Media Lab [22, 23].

3.4.3.2
The Sensor

Our Sensing Chair is equipped with a commercially available pressure distribution sensor called the Body Pressure Measurement System (BPMS) manufactured by Tekscan (South Boston, MA, USA). The office chair shown in Figure 3.4-1 is fitted with two sensor sheets (hidden inside the protective pouches) on the seatpan and the backrest. Each sensor sheet is an ultra-thin (0.10 mm) flexible printed circuit. The sensing units are arranged in 42 rows and 48 columns with an equal inter-element spacing of 1.016 cm. Each sensing point acts as a variable resistor in an electrical circuit – its resistance changes in inverse proportion to the pressure applied. This resistance is then converted to an 8-bit (0–255) digital value that corresponds to a pressure range of 0–4 psi. Each sensor sheet is attached to a multiplexing unit called a Handle (see Figure 3.4-1). The Handles for both sensor sheets can then be connected to a PC interface board that occupies a 16-bit ISA expansion slot of a personal computer.

The Tekscan BPMS system comes with a software environment where pressure distribution data from multiple Handles can be displayed in real time as color-coded two-dimensional maps. It also provides numerous functionalities including the recording of pressure maps as 'movies' for later viewing or analysis. The current version runs in a Windows 95/98 environment. This software is useful for checking the integrity of the sensor sheets and for gaining intuition about the structure of pressure distribution associated with various sitting postures.

The Sensing Chair project requires real-time access to pressure distribution data collected from the two sensor sheets. For that purpose, Tekscan provides a simple hardware interface API (application program interface). The Tekscan API is a 32-bit static library developed for the Microsoft Visual C++ 6.0 environment. It provides functions that enable a user, who may not have extensive knowledge of how to control and interface to the sensor hardware, to perform tasks such as initializing the sensor sheets, checking sensor parameters (number of rows and columns, and total number of sensor sheets), and capturing a frame of pressure distribution data in a buffer. The throughput sampling rate supported by the API can be up to 127 Hz.

The Tekscan BPMS system has been selected for several reasons. First, the inter-element resolution of the sensor sheets is 1.016 cm. This resolution is considered to be very high so as not to become the bottleneck of the performance of the Sensing Chair system. Another reason for using a sensor system with a higher

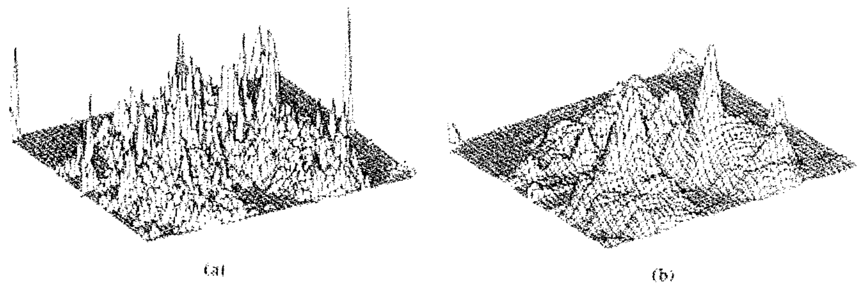

Fig. 3.4-4 3D views of a pressure map for the posture 'seated upright', (a) before and (b) after smoothing

than necessary resolution has to do with the integrity of the data: raw pressure readings can be very noisy (see spikes in Figure 3.4-4 a). Local averaging smooths raw data (see Figure 3.4-4 b) at the cost of reduced sensor resolution. This reduction in resolution is compensated for by the use of a sensor system with high resolution. Second, the sensor sheets are very thin (0.10 mm in thickness). The flexibility of the sheets makes it possible for them to conform to the shape of a chair. Third, the Tekscan pressure measurement systems are widely used by major research and industry laboratories including the Natick Army Research Laboratory (for the design of army boots) and Steelcase and Herman Miller (for chair evaluation). This enables us readily to compare our findings with those of other researchers. Finally, an important reason for our selection of the BPMS system is Tekscan's willingness to provide an API that has enabled us to access and process pressure distribution data in real time.

There are several known problems associated with the Tekscan BPMS system. Like any resistive sensors, the Tekscan sensors suffer from nonlinearity, nonuniformity, hysteresis, drift, temperature sensitivity, and limited sensor life. The noise introduced by these characteristics turned out to be manageable. Another problem with the sensor sheets is that they are designed for flat surfaces. When a person sits on a chair, the sensor sheet interfacing the person and the chair surface can bend, thereby introducing additional noise to sensor readings that are dependent on both the individual and the sitting postures. Repeated bending results in cracks in certain parts of the sensor sheets. When this happens, the entire sensor sheet needs to be replaced. An additional limitation of the Tekscan sensor is that it can only measure the pressure component that is perpendicular to the sensing elements. One can easily imagine how knowledge of pressure components that are tangential to chair surfaces can be useful in determining an occupant's sitting postures. Finally, the high cost of the Tekscan BPMS system has restricted its use to a handful of research systems.

3.4.3.3
Preprocessing of Pressure Data

The image shown in Figure 3.4-3 is a full pressure map for the static sitting posture of Left Leg Crossed (after noise removal). The top and bottom halves of the pressure map correspond to the pressure distribution on the backrest and seatpan, respectively. To understand the orientation of the pressure map, imagine standing in front of the chair and its occupant and unfolding the chair so that the backrest and the seatpan lie in the same plane. Therefore, the top, bottom, left, and right sides of the pressure map shown in Figure 3.4-3 correspond to the shoulder area, knee area, and right and left sides of the occupant, respectively. The size of each full pressure map is 84-by-48 (two sheets of 42-by-48 maps), or equivalently, 4032 sensels (sensing units).

As mentioned earlier, the raw pressure distribution map is typically noisy (spikes in Figure 3.4-4a). The noise is removed by convolving the pressure map with a 3-by-3 smoothing kernel:

$$\frac{1}{7}\begin{bmatrix} 0.5 & 1 & 0.5 \\ 1 & 1 & 1 \\ 0.5 & 1 & 0.5 \end{bmatrix}$$

The smoothed pressure map (Figure 3.4-4b) contains pressure artifacts (at the top left and right corners of the image) due to the corners of pressure sensor sheets being wrapped around the chair. Since these artifacts are common to all pressure maps, their removal is not necessary for the real-time posture tracking system that we have developed. Finally, although the sensor sheets can be calibrated to display pressure readings in psi or other standard units, the raw digital data are used since we are only interested in the *relative* pressure distribution on the chair surfaces. The raw pressure readings are normalized, separately for the seatpan and the backrest maps. The rest of the discussion on the Sensing Chair system assumes that all pressure maps have gone through the above-mentioned preprocessing procedures.

3.4.3.4
Static Sitting Posture Classification

To date, we have developed both a single-user [24, 25] and a multi-user [26] Static Posture Classification System (see Figure 3.4-2). For the multi-user system, a Static Posture Database has been collected on 30 subjects (15 females and 15 males) for 10 sitting postures. The subjects were selected with the goal of covering a wide distribution of anthropometric measurements. The ranges of subject's height, weight, and age were 152–191 cm, 45.5–118.2 kg, and 18–60 years, respectively. Each subject contributed five pressure distribution samples per posture. There are therefore a total of 150 training samples per posture, and the training database consists of a total of 1500 pressure distribution maps.

The postures contained in the Static Posture Database are (1) seated upright, (2) leaning forward, (3) leaning left, (4) leaning right, (5) right leg crossed, (6) left leg crossed, (7) leaning left with right leg crossed, (8) leaning right with left leg crossed, (9) leaning back, and (10) slouching. These postures are considered to be representative of the typical sitting postures that can be found in an office environment [27].

For each of the 10 postures, the 150 training samples are used to calculate the eigenspace for that posture (called an 'eigenposture space'). During classification, a new pressure distribution map is first tested for 'empty seat' by comparing the sum of all pixel values with a preset threshold. Once a pressure map has passed this initial test, it is projected on to the 10 eigenposture spaces. The posture label associated with the eigenposture space that best represents the new pressure map is then assigned to the new map. A more detailed description of our posture classification algorithm can be found in [26].

3.4.3.5
Performance Evaluation

The accuracy of our multi-user Static Posture Classification system was evaluated with additional pressure maps collected from two groups of subjects. First, an additional 200 pressure distribution maps were collected from 20 of the 30 subjects who contributed to the Static Posture Database (one sample per posture per subject). These pressure maps were then labeled with respect to their corresponding postures by the Static Posture Classification system. Figure 3.4-5 shows the classification accuracy in terms of percent-correct scores averaged over postures, as a function of the number of eigenvectors that are used in the classification algorithm (see [26] for details). As expected, overall classification accuracy increases as a function of the dimension of eigenposture space. The curve in Figure 3.4-5 shows a knee point at 15 eigenvectors with a corresponding average accuracy of 96.0%.

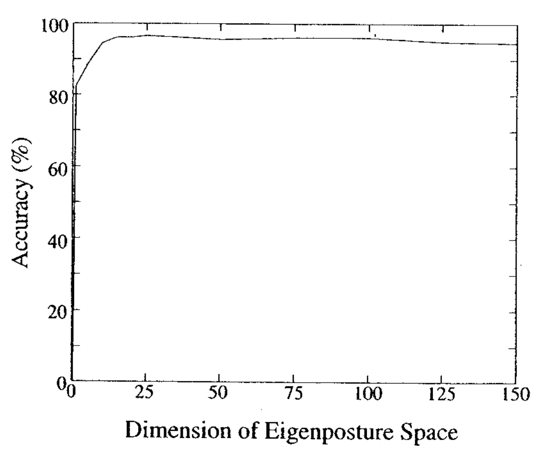

Fig. 3.4-5 Classification accuracy for 'familiar' subjects

Classification accuracy by posture (averaged across subjects) ranges from 90.3% (for posture 'leaning back') to 99.8% (for 'slouching'). The system is also able to discern among postures that have very similar pressure distribution maps (eg, 95.2% for 'leaning left', 95.1% for 'right leg crossed', and 93.5% for 'leaning left with right leg crossed').

Second, a total of 400 pressure distribution maps were collected from eight new subjects (five samples per posture per subject) who did not contribute to the Static Posture Database. The ranges of subject's height and weight were 160–191 cm and 65.9–93.6 kg, respectively. These anthropometric values are within those represented in the Static Posture Database. For these 'new' subjects that the system has never 'felt' before, the average classification accuracy at 15 eigenvectors dropped from 96.0 to 78.8%. In an effort to locate the sources of error, we examined the posture labels associated with not only the eigenposture space that best represents the test pressure map, but also those with the next two closest eigenposture spaces. The classification accuracies that can be potentially achieved if the correct posture label is associated with the first three closest eigenposture spaces turned out to be 99.0 and 97.5% for 'familiar' and 'new' subjects, respectively.

The execution time for the classification subroutine as a function of the number of eigenvectors used was also measured, with source codes that have yet to be optimized for speed. This is an important parameter for any real-time application of our system. The average classification time for 5, 10, 15, and 20 eigenvectors is 62.1, 107.8, 168.1, and 241.0 ms, respectively. The corresponding average classification accuracy (for 'familiar' subjects) is 88.5, 94.5, 96.0, and 96.0%, respectively. In view of these measurements, 15 (out of 150) eigenvectors corresponding to the 15 largest eigenvalues are used for our current version of the multi-user Static Posture Classification system.

3.4.4 The Sensing Floor System

3.4.4.1 Overview

The goal of the Sensing Floor project was to track single or multiple people by instrumenting floor panels. It takes advantage of a suspended floor structure where the weight of each floor panel is supported along its edges by aluminum railings (Figure 3.4-6). Force-sensing resistors (FSRs) are placed between the floor panels and their supporting structures. Readings from FSRs are then combined and compared to a threshold to determine whether a floor panel supports weight. While the overall concept is straightforward, sensor stability and accuracy turned out to be the limiting factors for the success of the Sensing Floor project.

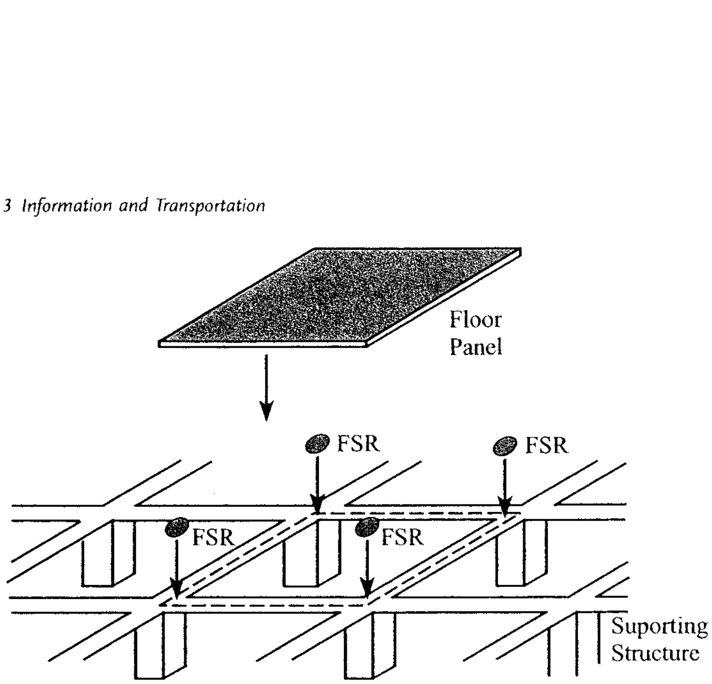

Fig. 3.4-6 An illustration of the sensing floor components. See text for details

3.4.4.2
The Sensor

The floor sensors are based on the FSRs manufactured by Interlink Electronics (Camarillo, CA, USA) (Part No. 402) [28]. Each sensor has a circular active sensing area that is 12.7 mm in diameter. It is interfaced with the floor panel and its supporting structure via rubber pads. Four sensors are used for each floor panel at its four corners. Each FSR is connected (as a variable resistor) to a measuring resistor in a simple force-to-voltage conversion configuration. The analog voltage level is then sent to a computer and digitized as an 8-bit integer.

The FSRs were selected for their ease of use and relatively low cost. The FSR User's Guide clearly states that 'FSRs are not suitable for precision measurements' and 'only qualitative results are generally obtainable' [28]. It was anticipated, however, that if a 2-bit accuracy per FSR channel could be achieved, then it would be possible to detect and track movements on the floor panels. In practice, we had considerable difficulties with sensor drift, thermal sensitivity, and hysteresis. It was difficult to compensate for random sensor variations as FSR readings would at times fluctuate as much as 50% in idle condition (that is, with no one standing or walking on the floor panels).

3.4.4.3
Data Processing

Real-time data acquisition is accomplished with a PC board that can support 64 analog inputs simultaneously at a sampling rate of up to 500 kHz (Part No. AT-MIO-64E-3, National Instruments). On-line data processing is performed with the LabVIEW software (National Instruments) that features a graphical-based programming environment. The initial implementation of the sensing floor included a total of 16^2 ft^2 floor panels (as limited by the 64-channel data acquisition system). Readings from the four sensors corresponding to the same floor panel are summed and compared with an empirically determined threshold. If the total force reading exceeds the threshold, an icon representing the floor panel will change its color from green to black on the computer screen. When sensor readings are stable, the system can correctly track a person walking across the active floor area.

3.4.5
The Future

We have described two systems based on distributed contact sensors. The Static Posture Classification system is based on a Sensing Chair that monitors the pressure distribution patterns on its surfaces in real time. Future work is aimed towards a Dynamic Posture Tracking system that continuously tracks not only steady-state (static) but also transitional (dynamic) sitting postures. It is expected that techniques such as hidden Markov modeling (HMM) commonly used for speech recognition can be successfully applied to sitting posture tracking. A robust posture tracking system to be completed in the near future will support many exciting applications such as a sitting posture monitoring system for ergonomics, and automatic adjustment of airbag deployment forces for automobiles.

The Sensing Floor system is based on floor panels instrumented with force-sensing resistors. Although we have demonstrated that it is possible to track people on the floor in real-time, we have had considerable difficulties with unstable readings from FSRs. Sensors that are more stable and accurate are needed in the future. It is conceivable that force-sensing units can be manufactured as an integral part of the floor structure to enable universal access to force distribution data on an active floor.

3.4.6
Acknowledgments

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