WristFlex: Low-Power Gesture Input with Wrist-Worn Pressure Sensors

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ABSTRACT

In this paper we present WristFlex, an always-available on-body gestural interface. Using an array of force sensitive resistors (FSRs) worn around the wrist, the interface can distinguish subtle finger pinch gestures with high accuracy (>80%) and speed. The system is trained to classify gestures from subtle tendon movements on the wrist. We demonstrate that WristFlex is a complete system that works wirelessly in real-time. The system is simple and light-weight in terms of power consumption and computational overhead. WristFlex's sensor power consumption is 60.7 μW, allowing the prototype to potentially last more then a week on a small lithium polymer battery. Also, WristFlex is small and non-obtrusive, and can be integrated into a wristwatch or a bracelet. We perform user studies to evaluate the accuracy, speed, and repeatability. We demonstrate that the number of gestures can be extended with orientation data from an accelerometer. We conclude by showing example applications.

Author Keywords
Gesture recognition; wrist interface; machine learning; FSR

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation: User Interfaces

INTRODUCTION
We envision a future where users have an ability to seamlessly control wearable devices and facilities in the environment. For that purpose, always-available on-body gestural interfaces will need to be developed. Such interfaces would be seamlessly worn on the body and ready to work at any moment, and in any situation.

To have better usability, the always-available gestural interface needs to satisfy four main criteria: First, such an interface should be *subtle*. The user should be able to use the interface in any scenario, without physical discomfort or embarrassment. The device should be small enough to be comfortably worn on the body without interfering with natural hand movements. Second, the interface should be *natural*. The gestures should be simple and intuitive, to avoid cognitive interference and fatigue. Third, the interface should be *low-power*. Users should not have to worry about constantly recharging the battery or carrying a large battery. There is a tradeoff between the power consumption and the complexity of the system; a low power interface will be light-weight and simple. Fourth, the interface should be *easily accessible*. It should be on-body, so users do not need to pull out a device from their pocket. The device should have one-hand input, so it can be used when the other hand can not be accessed.

Figure 1: WristFlex prototype. Left image: device worn on the wrist, while performing a finger pinch gesture. Right image: the side of the device that contacts the skin, exposing an array of force sensitive resistors (FSRs).

There is no existing device that can satisfy all the criteria of a seamless interface. So, the motivation of this paper is to satisfy those criteria. We present a gesture recognition system that uses pressure distribution around the wrist to discern finger movements. We find the wrist to be an attractive location for a future always-available interface. We are used to wearing wrist watches and bracelets, and the wrist is already used for a number of smart-phone-connected accessories such as the Galaxy Gear watch and the Fitbit activity monitor. The wrist is connected to the hand and fingers, therefore it could be used as a proxy for finger gestures. By putting sensors

on the wrist, your hand remains completely free for natural interactions.

The contributions of this paper are the following:

1. We present a novel, simple and low-cost gesture input system that can detect individual finger pinches from the pressure distribution around the wrist.

2. Using our wireless and real-time capable prototype, we perform user studies to assess its performance.

3. We optimize the power consumption of the device, so it can potentially last for a week on a single battery charge.

4. We explore broader interactions with the addition of an accelerometer and different usage scenarios.

RELATED WORK

In this section we will review the literature on always-available on-body input methods. On-body machine vision systems use wearable cameras to detect gestures. For example, Digits uses a wrist-worn 3D infrared camera to recognize finger gestures [10]. Another system used a time-of-flight camera [16]. Camera-based systems can not satisfy all the criteria of an always-available gesture system because of fundamental limitations. Cameras suffer from line-of-sight occlusions and have large power consumption and heavy computation requirements. Furthermore, privacy concerns might prevent a vision based approach from being always available.

Inertial based systems use accelerometer and gyro sensors to discern gestures. Some systems use off-body sensors such as Nintendo Wii remote [15]. Other systems use on-body sensors such as a glove [12] or rings [3] with accelerometer. Inertial sensors are low-power but have caveats e.g., they have to be worn on the fingers to sense finger movement. Such complications can reduce dexterity of the hands, therefore limiting physical interactions.

Brain-computer and muscle-computer interfaces detect neuronal electrical potentials and map them to gestures. A number of research projects explored electromyography (EMG), where electrodes are placed below the elbow to detect hand gestures [14]. Recently, a commercial product named Myo appeared that uses EMG for gesture detection [11]. Myo might have problems detecting finer finger gestures, because it uses less sensitive dry electrodes. EMG systems require the user to wear a bulky array of electrodes below the elbow, so they cannot be integrated with a wristwatch or a bracelet. Furthermore, EMG requires a high data rate and extensive signal processing, therefore it has high power consumption.

Bio-acoustic methods include detecting taps on different places on the skin [8], tapping fingers on surfaces [1], and performing hand motions [4]. Those methods might have problems with external noise and mapping of intuitive gestures to specific inputs.

Previous research showed some success with muscle activity recognition using arm-worn pressure sensors [2]. However,

we are not aware of any projects that explored finger gesture recognition from wrist-worn pressure sensors and developed a real-time system. Several projects focused on inferring finger and hand gestures from the wrist, and were inspirational for our work. Gesturewrist project looked at sensing capacitive changes around the wrist to detect gestures [13]. This method can be low power, but it was tested with two hand gestures, and did not distinguish individual finger movements. Similarly, another study placed photodiodes and infrared LEDs around the wrist to infer gestures from infrared reflectance [5]. This approach worked for classifying 8 hand gestures, but reflectance can be affected by sweat and dirt, and might not be energy efficient since it requires pulsing of high power infrared LEDs.
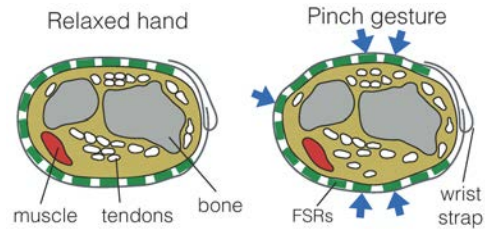

Figure 2: Sketch of the wrist cross section anatomy during two gestures. Individual FSRs are shown as green rectangles. The FSRs with the blue arrows are detecting higher pressures caused by the movements of tendons during a pinch gesture.

PRINCIPLE OF OPERATION

Pressure Sensing

We used force sensitive resistors (FSRs) for sensing pressure. Specifically, we chose the FSR400 (Interlink Electronics), because of small size and off-the-shelf availability. It is made from two copper traces that contact a sheet of conductive polymer. The resistance of the polymer decreases when pressure is applied, thus changing the resistance between the two copper traces. When no pressure is applied the polymer acts as an insulator. We chose to use FSRs because they have low power consumption, do not need complex interfacing and signal processing, are inexpensive, and small enough to fit the wrist.
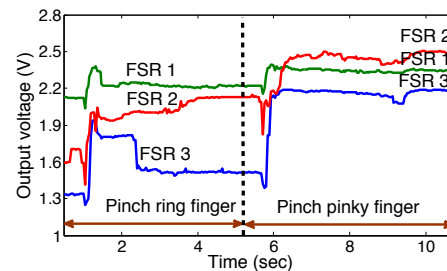

Figure 3: Differences in raw FSR readings at the wristband when pinching ring finger, and later pinky finger.

Gesture Recognition

The muscles that move the fingers and the hand are located mostly in the forearm. Fingers are connected through tendons

to those muscles. As sketched in Figure 2, the movement of tendons on the wrist slightly changes the shape of the wrist. Those changes can be detected with an array of pressure sensors. There is a unique pressure signature for each gesture. For example, Figure 3 shows raw data from three pressure sensors on the wrist when first pinching thumb and ring finger, and later thumb and pinky. These pressure distributions can be learned and used to classify new gestures. We pose this as a supervised machine learning task.
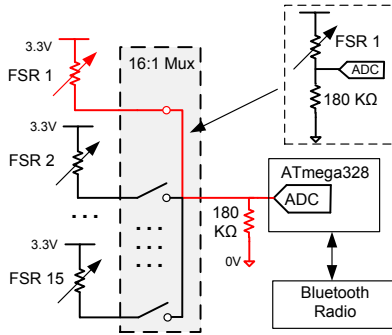

Figure 4: System diagram, showing sampling of FSR 1. The parts in red show the active circuit. This circuit can be simplified into a voltage divider, as shown in the right top corner. The gray rectangle is the multiplexer, showing 3 of 15 FSRs.

PROTOTYPE DESIGN

Hardware

As shown in Figure 1, we constructed a prototype that can be worn on the wrist. We made a custom Velcro wrist-strap to hold pressure sensors in place and to provide a tight contact between the pressure sensors and the wrist. As shown in Figure 5, a custom circuit board was made to fit the electronics.

An ATmega328 (Atmel) microcontroller was used to sample pressure sensors. The samples were transmitted to a laptop using a Bluetooth module (RN-42 Roving Networks). To allow real-time feedback to the user, data was sent at a 30 Hz rate. A 110 mAh lithium polymer battery was used for power. For more functionality, a 3-axis accelerometer ADXL335 (Analog Devices) was added.

We used 15 FSRs to densely cover as much of the circumference of a wrist as possible. As seen in Figure 4, FSR sensors were selected via a 16 to 1 multiplexer (CD74HC4067, Texas Instruments). The system is scalable to more or fewer sensors; they are read sequentially, so only one sensor is electrically connected at a time. Once active, the sensor became part of the voltage divider with a 180 KOhm resistor. Using one voltage divider for all sensors reduced power consumption by 15 times. The microcontroller's analog-to-digital converter (ADC) was connected to the output of the voltage divider.

We found that a 180 kOhm resistor provides enough range to sense gestures, while minimizing energy consumption. With a smaller resistors the range is bigger, but energy consumption is higher. An op-amp circuit should be added between the voltage divider and the ADC if using high sampling rate and a dynamic adjustment of the sensor's gain and range.

It was important to avoid mechanical strain and twisting of FSRs, since that can cause false pressure readings. We used long and flexible wires for connecting the sensors to provide strain relief. Also, we used wireless communications and a battery to avoid external communications and power cables.
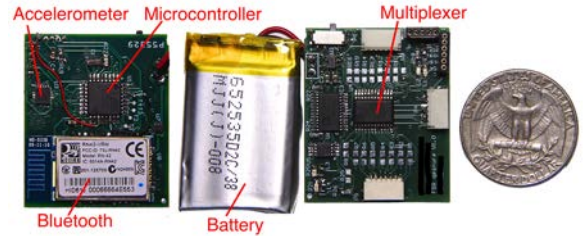

Figure 5: Circuit board: front and back. A U.S. Quarter is added for size comparison.

Machine Learning and Software

A Support Vector Machine (SVM) with a polynomial kernel was used for training and classification. We used Sequential Minimal Optimization (SMO) from the WEKA library [7], which is an optimized version of SVM. Instantaneous pressure readings were used as features. To exclude redundant and irrelevant sensors, correlation feature selection (CFS) was used. The classifier ran in real-time at 30 Hz. In this paper, the classifier ran on a laptop, but it can be adapted to a mobile device such as an Android phone.

As indicated in pilot studies, linear classification algorithms such as linear SVM and linear regression had low accuracy (about 30 to 50%) due to nonlinear output of FSRs and the voltage divider. A non-linear classifier, such as the polynomial SVM used here, was able to fit data better.

EVALUATION OF FINGER PINCH GESTURES

Setup

We recruited 10 participants (4 female, 6 male) to test 5 gestures. Ages ranged from 25 to 30 (mean: 27). As shown in Figure 6, gestures 1 to 4 involved pinching the thumb and one of the other fingers. Gesture 5 was hand in a relaxed position.

We picked this gesture set because pinching two fingers is subtle and involves only minor hand movements, hence the gesture set does not fatigue the user's hand. Also, pinch gestures are not socially obtrusive, they can be performed with hand-at-side, without drawing attention, and the finger pinch gestures are difficult to distinguish by other techniques such as EMG and vision-based techniques. We picked five gestures for this experiment, because it becomes difficult for the user to remember more. In the later section, we show how to increase the number of gestures.

Initially, each gesture was trained 3 times. To capture some pressure variations, each gesture was sampled 20 times for 2 sec interval. The training time was about 1 minute. After training, the participant was asked to practice gestures for about 2 minute to familiarize themselves with the system.

For the evaluation, participants were asked to do specific gestures from on-screen instructions. Each gesture was done 12

times, for a total of 60 gestures. Participants had to do each gesture for a 5-second period to make sure there was enough time to read and follow directions. The gestures were presented in a randomized order. Real-time feedback was provided for the first 30 gestures; the computer displayed what gesture it classified. No feedback was given for the last 30 gestures. The evaluation was done on the last 10 pressure readings in each 5 second period, which equates to an approximately 300 millisecond window.
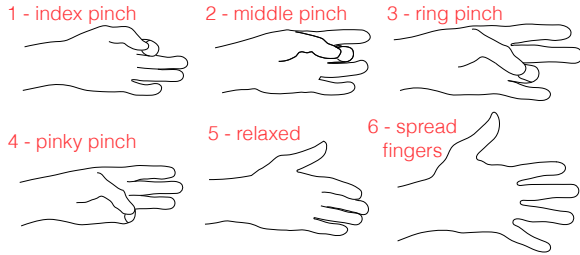

Figure 6: Gestures 1 to 5 were used in the finger-pinch experiment. Gesture 6 was used as a wake-up gesture.

Results and Discussion

Accuracy: Accuracy is defined as the number of correctly classified samples divided by the total number of samples. The accuracy due to chance was 20%. Off-line accuracy was computed using 10-fold cross-validation of the evaluation data. The mean accuracy across all participants was 96.3% (SD: $\pm 2.7\%$). Cross-validation represents the upper bound of accuracy. Also, we computed accuracy using the initial training data only, which reflects the real-time performance of the system. In this case, the accuracy was 80.5% (SD: $\pm 8.7\%$). With no feedback accuracy decreased to 69.3% when using training data, and remained the same with cross-validation (96.3%). As seen in Figure 8, misclassification occurred most often in the index finger pinch, likely because tendons connected to the index finger were not fully covered by the sensors. As shown shown in Figure 7, that area was covered by the band's fastening strap. The relaxed hand position and pinky pinch was rarely misclassified.

Sensor contributions: Correlation feature selection showed that the number of relevant FSR sensors varied from 4 to 11 (mean: 7.1). As shown in Figure 7, sensors on top of the wrist were more relevant than on the bottom; tendons on the top are near the skin, while tendons on the bottom are bundled together and are deeper. Also, sensors located near muscles were relevant, thus likely contributed to high classification rate of pinky pinch.

Pinch force: The force between fingers during pinch gestures was measured to be between 20 and 169 grams. The measurement was done by calibrated FSR located between the two fingertips. We were concerned that wearing the system can cause discomfort, since FSRs need to be in tight contact with the skin, but none of the participants reported discomfort during the short studies. But, sweating under the band could be uncomfortable during prolonged wear (>2hours).
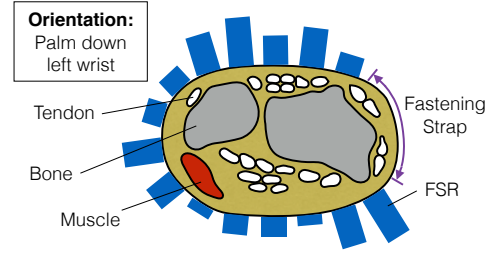

Figure 7: Cross section of the wrist. FSRs are shown in their approximate locations, with heights proportional to the number of times particular FSR was selected as a feature by CFS.

Speed: An important consideration is how fast gestures can be performed. In practice gestures could be performed faster than the allocated 5 seconds. It took a mean of 1.60 sec (SD: ± 0.28 sec) to classify a new gesture from the time the command to do the gesture was given to stable classification of gesture by the real-time classifier. The main limitation is the settling time of FSRs, because movements between gestures create large pressure variations that are picked up by FSRs.

Reproducibility: The user should be able to remove the device from the wrist and put it back, without the need to retrain the classifier. We tested reproducibility by removing and putting the device back 3 times for 3 participants, and performing finger pinch experiment during each trial. Participant was provided with immediate feedback. The same initial training data was used in 3 trials. Mean accuracy decreased as trials progressed: 83.2%, 73.3%, and lastly 67.5%. Our results show the low end of accuracy as there was no guidance or calibration mechanisms. Also, applying consistent tightness using Velco strap was especially problematic. The decrease of accuracy was mostly due to completely losing 1 or 2 gestures; as the training data was too rigid to account for tightness. With a calibration mechanics and an automated way to guide sensor placement, no retraining should be needed.
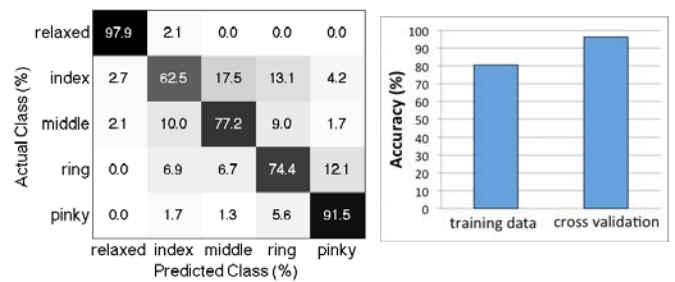

Figure 8: Finger-pinch experiment results. Left: confusion matrix for accuracies using training data. Right: accuracy using training data and cross-validation.

ADDITIONAL GESTURES WITH ACCELEROMETER

The same set of gestures could be identified differently by rotating the hand. In this experiment by using two different hand orientations, we increase the number of gestures from 5 to 10. The advantage of an accelerometer is low power; it adds only 72.6μW to the system's power consumption.

We created an assembly of three SVM classifiers: one for the accelerometer and two for the pressure. The accelerometer classifier used 3 features: accelerations in the X, Y, and Z axis. The pressure classifier was the same as before. Based on the orientation (accelerometer) classifier, one of the two pressure classifiers is activated. We used 3 separate classifiers to avoid the problem of uneven feature sizes: accelerometer had only 3 features, while pressure has up to 15 features.

We recruited 3 participants (1 female, 2 males, age 27-30) for the experiment. A set of 10 gestures was tested. We used the same pinch gestures as before. One set was performed with palm facing the hip, so the palm is parallel to the hip. In the second set the hand was rotated 45 degrees, to be perpendicular to the hip. Each gesture was performed 12 times. Feedback was provided. The accuracy with 10-fold cross-validation was 94.4% (SD: ± 13.14%), and 73.9% (SD: ± 17.5%) when using training data only. Accuracy due to chance was 10 %.

LOW POWER OPERATION

Power consumption is an important parameter for on-body and always-available devices. Lower power consumption allows for smaller size and longer operation. Because of the multiplexer, only one FSR is active at any moment. As a result, the voltage divider consumes 60.4μW in a worst case scenario, when the FSR resistance is zero. The multiplexer consumes a maximum of 0.33μW. Therefore, the total power consumption of analog circuitry and sensors is 60.7μW. In comparison, in a state-of-the-art wrist-worn camera-based gesture system [10] the camera itself consumes 60mW, which is at least 3 orders of magnitude higher.

Increasing microcontroller clock speed greatly increases the power consumption. We run the clock at a low speed of 1 MHz, which is sufficient here, because the microcontroller does not need to do any math operations such as filtering. It is only used to sample and send the data. This shows how a light-weight sensing system can save energy. At that speed, microcontroller consumes 2.9mW. The Bluetooth module is the most energy intensive part, requiring a transmission rate of 30 Hz for a real-time operation. At that rate, the Bluetooth consumes 93.1mW. The total power consumption of 96.0mW, allows for 4 hours of continuous wireless operation. A lighter-weight radio (e.g., Bluetooth Low Energy) could reduce the power consumption further.

In a real-world application, the device would be used only occasionally, and should be asleep most of the time. We used a spread-finger gesture, shown in Figure 6, to wake up the device. Once awake, the device will operate continuously and transmit data through the Bluetooth. If no new gestures are detected the device will go back to sleep. During sleep, the system wakes up every 2 seconds to check the pressure readings, and decide to continue sleep or to wake up. The classification of the wake up gesture is done locally on the microcontroller, so data is not send to a laptop for processing. The total energy consumption during sleep mode is 185.0μW. If the device is used for 30 minutes a day, the operation time could be increased to 7 days.

FALSE POSITIVES

If the interface is worn in everyday life, it will be important to avoid false positives; accidental recognition of gestures. Besides reducing energy consumption, wake up gesture has a purpose of unlocking the device; the device would only work once intentionally unlocked. The wake up gesture has higher mean FSR value, than all gestures and hand movements we tested. The wake up gesture was tested during the finger-pinch experiment, and could be detected with a 100% accuracy by thresholding of mean value of all FSRs. Also, as previously proposed in [4], a possible way to prevent false positives is to activate gestures only in specific hand orientation, such as when hand is pointing down.

Figure 9: Example applications. Left: controlling two red-green-blue (RGB) lamps. Right: controlling bicycle lights.

EXAMPLE APPLICATIONS AND GESTURE SPACE

To illustrate the real-time performance and to understand the gesture space we developed two applications. The applications are shown in Figure 9, and in the accompanying video.

1. Remote controller application: The 4 pinch gestures can be used as 4 virtual buttons for interaction with external devices, such as a phone or an appliance. Running on the top of the classifier, we developed software that translates finger pinch gestures into button presses. To settle pressure variability, software outputs a button press only if the classifier outputs 10 same gestures in a row. We developed an application to address and control two RGB lamps. The activation gesture is used to connect to the lamps. Using the index and the middle finger pinch gestures, the user cycles and selects which lamp to modify. The selected lamp provides feedback by flashing, and final selection is confirmed with the pinky pinch. Once selected, 3 pinch gestures are used to switch between red, green or blue colors. Finally, with a pinky pinch, the function of the buttons changes and pinches adjust the brightness and turn on/off the lamp.

2. Context awareness app: The system can be trained to detect natural gestures (e.g, hand postures during actions), and infer context. We developed an application for bicycle riders, where wearable lights are controlled by the device. Such app as can enhance safety for riders at night by dynamically controlling the lights. When the rider's hand engages the break handle, the stop light turns on. Also, when the user is gripping handlebars, the lights turn on automatically. Finally, left or right blinkers can be turned on by lifting the middle or pinky fingers.

2. Continuous gestures: As our explorations indicate, the device can track the rotations of the hand. This could provide a 2D input similar to a computer mouse. Also, in the

pinch gesture, it is possible to discern how hard two fingers are pressed, therefore adding continuous gestures to pinches. This could add another dimension to pinch gestures, which would be useful in, e.g., controlling volume or zoom.

LIMITATIONS AND FUTURE WORK

Gestures: As mentioned above, the rotation of the hand and pressure variations in pinch gestures could be used as continuous gestures. However, they will cause misclassifications in the discrete pinch gestures. It is part of our future work to develop a mechanism to reliably transition between the continuous and discrete gestures.

Machine learning: We found that each participant needed unique training data; the classifier can not yet generalize the pinch gestures. Also, if gestures are trained using one hand orientation and position, they might not work in a different hand position. To alleviate those issues the classifier should take into account the biomechanics of the hand, and use an inertial measurement unit (IMU) to sense and compensate for different hand positions. Furthermore, in real-life the device might rotate during wear, thus the classifier should be rotation-invariant.

Sensors: We used off-the-shelf FSRs that were not designed for this wearable application. They are relatively large, require assembly into an array, and are affected by sweat and humidity. Using custom-made dense matrix of small pressure sensors would result in higher accuracies, since it will pick up finer pressure variations and cover larger area. Currently, such a matrix can be commercially printed with the FSR ink (e.g., [6]), but the cost and prototyping time is high. Alternatively, FSR arrays can be prototyped using conductive ink-jet technology [9] and Velostat as a pressure-sensitive semiconductor. To prevent effects from sweat and humidity FSRs can be sealed in a waterproof material. Also, a calibration mechanism could be added to compensate for those effects, such as with a skin conductance or temperature sensors. We plan to develop custom FSRs for quick and inexpensive prototyping.

CONCLUSION

In this paper we presented WristFlex, a novel gesture recognition device that uses wrist-worn pressure sensors. We show that the system can detect finger pinch gestures in real-time with high accuracy (>80%) and speed (1.6 sec). Also, we demonstrated the addition of an accelerometer to greatly extend the number of gestures. Furthermore, we explored interaction scenarios such as using of the system to control lighting and context sensing for bicycle riders. The system is attractive for always-available one-hand gesture input. The system has low power consumption; the current prototype can potentially last for a week on a single charge. The device is unobtrusive; it can be made into a small wrist-worm bracelet. Custom pressure sensor arrays can be prototyped with an off-the-shelf printer and conductive ink or commercially with FSR ink. WristFlex is a viable alternative to EMG and camera-based approaches.

ACKNOWLEDGMENTS

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