Clustering Analysis of Acoustic Emission Signals during Compression Tests in Mille-Feuille Structure Materials

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Acoustic emission (AE) methods with supervised and unsupervised machine learning were applied to investigate deformation behaviors of Mg–Y–Zn alloys and Ti–12Mo alloy with mille-feuille-like structure. In the supervised learning process, AE signals received from compression tests with pure magnesium and directionally solidified (DS) Mg12Zn12Y3 alloy with long-period stacking ordered (LPSO) structure were used as the training data to build a classification model for classifying AE sources from α-Mg phase and LPSO phase in Mg–Y–Zn alloys. In the unsupervised learning process, AE signals data from Ti–12Mo alloy were divided into two clusters according to the frequency spectrum features, and digital image correlation (DIC) was carried out to study those clusters and deformation behaviors. Deformation behavior of Mg–Y–Zn alloys and Ti–12Mo alloy were compared and discussed, and the method of applying AE with supervised and unsupervised machine learning was evaluated. [doi:10.2320/matertrans.MT-M20211105]

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1. Introduction

Acoustic emission (AE) as an in-situ technique has the possibility to provide insight into individual deformation mechanisms and related to specific stages of the deformation curve concurrently with the deformation tests.1) For this reason, AE has been widely used in research studying deformation behaviors of materials.2–4) AE is the phenomenon of rapid release of elastic waves in solids that occurs when a material undergoes irreversible changes in its internal structure. The classical approach for evaluation of AE data includes extracting AE events by setting threshold level and hit definition time. However, it is inappropriate if distinguishing between the AE signals from various sources is required. Some researches have been achieved by researchers based on AE combined with machine learning.5–7) Garcés et al.5) applied adaptive sequential k-means (ASK) procedure for data evaluation and identified AE clusters by checking the time of the appearance of the events in a given cluster and inspecting of characteristic parameters of the power spectral density (PSD) in Mg–Y–Zn alloys. Muto et al.7) identified AE clusters sources by comparing the obtained AE signals from kink deformation and clustering results divided by principal component analysis (PCA) and k-means in Mg–Y–Zn alloys. Although machine learning has been widely used in the analysis of AE behavior, the identification of AE sources is still a complex task in unsupervised machine learning. In the application of supervised machine learning, obtaining training data also becomes a challenge.

Magnesium alloys are promising structural materials due to their high specific strength and high specific stiffness.5) Increasing social awareness of the need for energy-saving and material recyclability, as well as the effect of intense environmental pressures9) make Mg–Y–Zn alloys with LPSO structure attracting more and more attention from researchers since its discovery by Kawamura et al.10) in 2001. The Mg/ LPSO microstructures are generally viewed as “mille-feuille structure” through the stacking of hard and soft layers which makes Mg–Y–Zn alloys have high mechanical performance potentially exhibiting a high yield strength of about 610 MPa and 5% of elongation at room temperature11) while applications of traditional magnesium alloys have been limited because of their poor corrosion resistance, poor ductility and low mechanical and creep resistance.3,10–14) A characteristic deformation mechanism in the LPSO phase of Mg–Y–Zn alloy is the kink deformation which consequently forms structures of kink bands.13,15,16) Hagihara et al. investigated the role of the deformation kink on the mechanical properties of Mg alloys with LPSO structure and clarified that kink band strengthening is one of the predominant mechanisms for high yield stress of those alloys.13) Inamura et al.18) explained the geometry of kink bands with the general shear direction on the unique slip plane based on rank-1 connection. It is worth noting that kink deformation was also found in other metals such as Cd19) and Zn.20) Inducing kink deformation in other metals by introducing mille-feuille structure has also become a method to investigate the mechanisms of kink band formation and kink band strengthening. Titanium and its alloys are popular research topics due to their attractive properties, such as high specific strength and corrosion resistance, good surface quality and low cost.21–24) There are increasing number of researchers trying to induce kink deformation in titanium alloys,25,26) but the strengthening by kink band formation has not been confirmed in titanium alloys. Emura et al.27) applied slight cold rolling with the reduction rate of 5% and subsequent aging heat treatment at 973 K for 180 ks on Ti–12Mo alloys and introduced a mille-feuille-like α/β layered structure successfully. Further study is demanded to investigate whether kink deformation can occur in this kind of Ti alloy.

In this study, the deformation behaviors of different phases in extruded Mg–Y–Zn alloys and Ti–12Mo alloy with mille-feuille-like structure were studied with AE and machine learning. In our previous work,4) AE events were detected by
M304A AE sensors. However, since AE signals present specific characteristics in ultrasonic range (several tens of kHz to several MHz), there are risks of reducing the machine learning accuracy by applying resonance model AE sensors. To improve the machine learning performance, wide bandwidth model AE sensor of 1045S AE sensors are used. The kink band formation is discussed through the comparison of the results obtained from Mg-Y-Zn alloys and Ti-12Mo alloy. Methods of analyzing AE with supervised and unsupervised machine learning are evaluated eventually.

2. Analytical Procedure

2.1 Supervised clustering of AE signals

The supervised machine learning method of support vector machine (SVM) was performed to investigate AE signals from Mg97Zn1Y2 alloy and Mg89Zn4Y7 alloy in this study as shown in Fig. 1. Pure magnesium and LPSO DS alloy are single phase materials while Mg97Zn1Y2 alloy and Mg89Zn4Y7 alloy are two-phase materials that are composed of α-Mg phase and LPSO phase. The characteristics of AE signals from the same component are supposed to be consistent, so AE signals from compression test with pure magnesium and LPSO alloy are used as teacher data in this study. SVM constructs hyperplanes in a high-dimensional space, which can be used for classification, regression, or other tasks like outliers detection, which makes it widely used in acoustic signal processing. Normalized intensities from 100 kHz to 1000 kHz of AE frequency spectrum obtained by fast Fourier transform (FFT) were used as the parameter.

During the SVM clustering process, AE signals from pure magnesium and directionally solidified Mg97Zn1Y2 alloy (DS LPSO alloy) were defined as α-Mg phase cluster and LPSO phase cluster, respectively. The cross-validation method was applied to build a SVM model with AE signals of those two classes. In this procedure, 60% of AE signal data were selected randomly from the total data pool to the training data, which were attached with a known label, while the rest data were treated as the testing data to verify the accuracy of the model. The accuracy was assessed by the ratio of whether the predicted labels consisted to the original label in the test data. The training and testing process was repeated until the accuracy exceeded 80%. In order to obtain a model with high quality, the built SVM model was verified with AE signals from additional pure magnesium and DS LPSO alloy specimens. AE signals of Mg97Zn1Y2 alloy and Mg89Zn4Y7 alloy were finally divided into classes of α-Mg phase and LPSO phase by the model.

2.2 Unsupervised clustering of AE signals

The unsupervised machine learning of k-means was applied for studying AE signals from Ti-12Mo alloy as shown in Fig. 2. K-means is a method of vector quantization that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. The best cluster number was decided by sum of squared error (SSE) of all AE data from compression test with Ti-12Mo alloy. SSE was a measure of the discrepancy between the data and an estimation model and the best cluster number of k is the turning point in the SSE curve. SSE can be got as in the following equation:

$$SSE_k = \sum_{i=1}^{n} \sum_{j=1}^{m} (y_i - x_j)^2$$

where $SSE_k$ is the SSE value with cluster number of k, $y_i$ is the value of the i-th predicted cluster center during the calculation, $x_j$ is the value of j-th element in the i-th predicted cluster.

AE data were divided into certain clusters decided by SSE. Then, clusters were identified as noise and deformation mechanisms according to AE frequency spectrum and the synchronization between AE behaviors and deformation behaviors.

3. Experimental Procedure

3.1 Materials

Materials used in this study included pure magnesium, DS LPSO alloy, Mg97Zn1Y2 alloy and Mg89Zn4Y7 alloy and Ti-
12Mo alloy as shown in Fig. 3. The pure magnesium was cut from a commercial extruded magnesium bar with diameter of 10 mm and annealed at 500°C for 30 minutes with a constant heating rate of 5°C/min. The DS LPSO alloy mainly composed of LPSO phase was received in directionally solidified state by the Bridgman method at a solidification rate of 10 mm/h under an argon atmosphere. Mg97Zn1Y2 alloy and Mg89Zn4Y7 alloy with LPSO phase volume fractions of 25% and 85% respectively were hot-extruded with an extrusion rate of 10 at a temperature of 450°C. Ti–12Mo was slight cold rolling with the reduction rate of 5% and treated with aging heat treatment at 973 K for 180 ks.27)

3.2 Compression tests and surface observation

The compression tests were performed by the AG-100 kN testing machine with a displacement rate of $5.00 \times 10^{-4}$ mm/s at room temperature. Specimens were compressed in the direction of the plastic-work or DS solidification process depended on the type of materials by two jigs, inside which two AE sensors were attached. Specifically, the compression test of Ti–12Mo was cyclic loading and unloading and the end stress of each cycle was 100 MPa higher than the previous one. All specimens were machined into cubes with an edge length of 5 mm and one side polished for observation. The microstructures of all specimens were examined by optical microscopy. Ti–12Mo was further investigated by electron backscatter diffraction (EBSD).

In order to identify AE from Ti–12Mo alloy, digital image correlation32) (DIC) was performed by Ncorr.33,34) The subset spacing parameter was set to 1 pixel to analyze images with the original image size. 4 pixels were used for the bilinear interpolation for the strain calculation process.

3.3 AE measurement

The schematic of AE measurement in this study is shown in Fig. 4. Different to our previous work,4) AE signals are detected by 1045S AE sensor made by Fuji ceramics in this study. Compared with M304A AE sensor, 1045S AE sensor has a wider resonance frequency band varying from 200 kHz to 1300 kHz which matches the AE frequency range better and provides more comprehensive characteristics of AE events. AE signals of pure magnesium and DS LPSO alloy
were amplified by 20 dB amplifiers while 40 dB amplifiers were used in compression tests with \( \text{Mg}_{97}\text{Zn}_{1}\text{Y}_{2} \) alloy, \( \text{Mg}_{89}\text{Zn}_{4}\text{Y}_{7} \) alloy and Ti–12Mo alloy according to the AE signal intensity. AE events were measured by continuous-wave-memory (CWM) developed by our group.\(^{35} \) The high pass filter was set to 100 kHz and the threshold was set to 38 dB according to the experiment condition. Noise signals were further excluded by the inverse calculation, in which AE signal was regarded as noise when its source location was out of the specimen. The source location was calculated as in the following equation:

\[
y = \frac{v_m(t_1 - t_2)}{2}
\]

where \( y \) is the relative distance from source location to the center of the specimen of one AE event, \( v_m \) is the sound velocity of the material, \( t_1 \) and \( t_2 \) are the time when AE signals reach the two AE sensors, respectively. The time was calculated by two-step Akaike’s information criterion (AIC). When value of \( y \) was larger than the half of side length of the specimen, the AE signal was regarded as noise signal.

The AE energy was calculated according to the waveform spectrum of each AE event as in the following equation:

\[
E = \int_{t_1}^{t_2} V^2(t)dt
\]

where \( E \) is the energy of one AE event, \( V(t) \) is the voltage of AE signal, \( t_1 \) is occurrence time and \( t_2 \) is the time when AE signal crosses the threshold last time.

4. Results and Discussion

4.1 Analysis of deformation behavior in Mg–Y–Zn alloys with supervised clustering

The average grain size of pure magnesium was approximately 1100 µm. The grains of DS LPSO alloy present plate-like shape with a width of approximately 200 µm. In the \( \text{Mg}_{97}\text{Zn}_{1}\text{Y}_{2} \) alloy, LPSO phase exhibited a long strip shape with a width of approximately 4 µm. In the \( \text{Mg}_{89}\text{Zn}_{4}\text{Y}_{7} \) alloy, \( \alpha\)-Mg phase exhibited an irregular block shape with a width of approximately 6 µm. Optical micrography after compression tests of specimens are shown in Fig. 5. After compression, twin bands were found in the pure magnesium in Fig. 5(a). Kink bands were observed in shape of dense black triangle structure in the DS LPSO alloy in Fig. 5(b). Similarly, deformation lines were formed in \( \text{Mg}_{97}\text{Zn}_{1}\text{Y}_{2} \) alloy while typical kink bands were formed in \( \text{Mg}_{89}\text{Zn}_{4}\text{Y}_{7} \) alloy.

The stress-time curve, AE event number and AE energy distribution during compression test with all specimens are shown in Fig. 6. In pure magnesium (Fig. 6(a)), the yield stress was approximately 33 MPa, and work hardening happened after yielding. The number of AE event started increasing at early stage and rise quickly when stress reached the yield stress. Few AE signals generated during the strain hardening process. AE signals with high energy concentrated on the yield point.

In the DS LPSO alloy shown in Fig. 6(b), the yield stress was approximately 200 MPa. The number of AE events was less than in pure magnesium. In particular, after the yield
point, new AE signals stopped generating suddenly. Most AE signals had relatively low energy of under 4000 V²·µs.

AE behaviors of M₉₇Z₈Y₂ and M₈₉Z₄Y₇ alloys were quite different as shown in Fig. 6(c) and Fig. 6(d). In M₉₇Z₈Y₂ alloy, most AE signals concentrated on the yield point. In the following strain hardening process, there was no AE signal occurring. In the M₈₉Z₄Y₇ alloy, AE event number started increasing at low stress level and most AE signals generated after the yield stress. The total amount rise until the specimen failed. AE signals with high energy concentrated on the beginning of the strain hardening process.

Normalized frequency spectrums, stress-time curve, AE event number and energy of α-Mg phase class and LPSO phase class divided by SVM are shown in Fig. 7 and Fig. 8. Differences could be found at 650 kHz and 900 kHz. The SVM model could distinguish AE signal source with high accuracies as shown in Table 1. In M₉₇Z₈Y₂ alloy, the number of AE events of α-Mg phase class was higher than that of LPSO phase class, which could be the evidence of more active deformations in α-Mg phase. Both classes shared a similar trend during the compressing process. In M₈₉Z₄Y₇ alloy, due to a higher volume fraction of the LPSO phase, the number of AE event of LPSO phase class was almost equal to that of α-Mg phase. AE event of LPSO phase class kept generating in the whole strain hardening process while AE event of α-Mg phase only activated at the first half of the hardening process.

The mixed composition of α-Mg phase and LPSO phase greatly improves the strength and elongation of the M₉₇Z₈Y₂ alloy and M₈₉Z₄Y₇ alloy. In addition, the different volume fraction of LPSO phase lead to significant differences in the stress-time curve. In the aspect of AE, curves of AE event number and time of pure magnesium and M₉₇Z₈Y₂ alloy show similar trends. Conversely, AE signals of M₈₉Z₄Y₇ alloy behave differently from that of DS LPSO alloy even if M₈₉Z₄Y₇ alloy was composed by 85% of LPSO phase, which is assumed to be caused by the difference in microstructure.

In the machine learning results, the SVM model can keep good consistency when testing AE data of the same type of material. However, the verifying results with specimens in additional compression tests are not as high as the accuracy obtained in the model training process as shown in Table 1.
due to the reason that both α-Mg phase and LPSO phase in Mg–Y–Zn alloys share same deformation mechanisms. Accuracy for predicting AE data from DS LPSO alloy was much lower than that of pure magnesium indicating higher rate of AE signals released by shared mechanisms in the DS LPSO alloy.

In our previous work, the AE signals generated by nucleation of twinning in pure magnesium and formation of kink bands in DS LPSO phase alloy are obtained by combining AE measurement with in-situ surface observation and are used for studying the deformation behaviors of extruded Mg97Zn1Y2 alloy and extruded Mg89Zn4Y7 alloy. In this study, the AE sensors with wide resonance bands are used instead of 304A AE sensors and direct observations on deformed areas are not performed with Mg–Y–Zn alloys. In addition, data used for machine learning are AE signals from the compression tests in pure magnesium and DS LPSO phase alloy in place of specific AE signals of deformation twin or kink. Interestingly, despite the existence of those differences in research methods, the behaviors of α-Mg phase class and twin class, as well as the LPSO phase class and kink class, are highly similar. There is a similar trend between the AE number of kink and AE number of LPSO phase class, but the part of the former is not presented when the stress exceeds 700 MPa. The AE signals number of α-Mg phase class are higher than that of LPSO phase class when the compression test ends, which is contrary to the relation of AE event rate of twin and kink. By focusing on the early deformation stage, the detailed AE behavior of α-Mg phase class and LPSO phase class in the Mg97Zn1Y2 alloy and Mg89Zn4Y7 alloy at early stage can be studied as shown in Fig. 8. In the Mg97Zn1Y2 alloy, AE event of α-Mg phase class begins to increase when stress is approximately 75 MPa while AE event of LPSO phase class increases near 150 MPa. In the Mg89Zn4Y7 alloy, there is a significant increase in AE events of LPSO phase class at 75 MPa, and the increase stops at 180 MPa while AE events of α-Mg phase class begin to increase slowly from 180 MPa to 380 MPa. After a period with nearly no AE signal detected, AE events of α-Mg phase class rise quickly again near 500 MPa. AE events of LPSO phase class begin to increase quickly at 550 MPa. However, those changes in the AE number at early deformation stage is not found in the AE event rate of twin and kink. Since the loading direction is parallel to the solidification direction which is perpendicular to the (0001) orientation, the schmid factor for the basal slip is negligible in LPSO phase, which means basal slip in LPSO phase is suppressed during compression process. Hence, AE signals of LPSO phase cluster are supposed to be mainly composed by AE signals of kink deformation, which could be the reason why the behaviors of both LPSO phase cluster and kink class are highly resemble. Besides, the AE behaviors of twins and α-Mg phase class are also very similar to each other, which suggests that deformation twin is the principal deformation.

### Table 1 Accuracy of the SVM model.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Training data</th>
<th>Verifying data</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pure Mg.1</td>
<td>Pure Mg.2</td>
<td>Pure Mg.3</td>
<td>96.8%</td>
</tr>
<tr>
<td>DS LPSO alloy _1</td>
<td>95.0%</td>
<td>92.4%</td>
<td>77.2%</td>
</tr>
<tr>
<td>DS LPSO alloy _2</td>
<td>91.3%</td>
<td>76.0%</td>
<td></td>
</tr>
<tr>
<td>DS LPSO alloy _3</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

The AE behaviors of twins and α-Mg phase class are also very similar to each other, which suggests that deformation twin is the principal deformation.
mechanism during the compression process in the ω-Mg phase. AE signals of ω-Mg phase class should also contain signal released by slip. The comparison proves that with a wide resonance band, 1045S AE sensor can capture more detailed features of AE signals which consequently improves the accuracy of machine learning process, which is assumed to be the reason why the AE behaviors at the early stage of compression test detected in this study.

4.2 Analysis of deformation behavior in Ti–Mo alloys with unsupervised clustering

Ti–12Mo exhibits a lamellar structure of ω phase (black phase) and β phase (grey phase) with uneven thickness, and between each two black linear ω phases, β precipitates are distributed as dotted or short linear shapes. The average grain size of β phase is approximately 300 µm and the average thickness of ω phase is approximately 0.4 µm. Optical micrography after compression tests of Ti–12Mo alloy was shown in Fig. 5(e), in which slender deformation lines formed in the ω phase precipitates on the boundary of β twin are mainly distributed along several directions. At the same time, deformation bands along the same direction are parallel to each other, forming a local mille-feuille structure. DIC analysis on the same region of each compression cycles are shown in Fig. 9. Slight deformations bands were observed at 500 MPa along the area in light-yellow color which gradually deepened with the stress increasing and extended to the whole β grain eventually. It is noteworthy that region with severe deformation in red color occurred at 600 MPa concentrating on the ω phase precipitates. EBSD map of specimen at 1000 MPa is shown in Fig. 10. Deformation regions on the observed surface with white bright line in Fig. 10(a). In the meantime, these deformed regions can be found in the EBSD results in Fig. 10(b) and Fig. 10(c), which became the evidence that deformations mainly form in the ω phase precipitates. Therefore, in the DIC analysis result, areas showing severe deformation in red color are supposed to be the ω phase precipitates. Deformation kink band is not found in those regions during the compression test. Instead, severer slips happened in ω phase precipitates. The DIC analysis showed a high level of stress concentration on dotted ω phase precipitates which becomes the restriction of the kink band formation process. In order to investigate these factors, Ti alloys with clearer ω/β layered structure are under researching.

The stress-time curve, AE event number and AE energy distribution during compression test with Ti–12Mo alloy was shown in Fig. 6(e). AE behaviors of ten compression cycles were stitched together by time sequence. AE events were most active in the cycle-5, cycle-6, cycle-7 and cycle-8. The high energy AE signals first increased and then decreased with the compressing cycle increasing. To exclude noise, AE signals are divided into two groups decided SSE-k value curve as shown in Fig. 11(a). In Fig. 11(b), it can be found that events of cluster 2 started accumulating at extremely low stress level before the launching of the straining and distributed more uniformly with stress increasing compared with cluster 1. In addition, the frequency spectrum of cluster 2 (Fig. 11(c)) showed a low intensity and a low energy above 300 kHz, which was a
typical characteristic of mechanic noise.\textsuperscript{3} Hence, AE signals of cluster 2 were excluded from the AE data pool as noise. AE event number curve shown in the Fig. 6(e) is consisted of AE signals of cluster 1. AE signals of cluster 1 were classified again by the k-means method with cluster number of two decided by SSE-k value curve in Fig. 11(d). In terms of the increment of the AE signals number, two clusters behaved differently in certain compressing cycles. Clear differences could also be found in the relative intensity spectrum at around 550 kHz and 900 kHz in Fig. 11(f).

From the DIC analysis shown in Fig. 9, it can be found that strain mainly concentrates on the elongated $\beta$ twin strips with a large deviation from compressing direction. In addition, new deformation twin band is not found in the Ti–12Mo during the compression test, which is assumed to be due to the existence of $\alpha$ phase precipitates that wrapped around the edge of $\beta$ twin strips and distribute inside the $\beta$ grains densely blocks the formation of deformation twin band in $\beta$ phase. However, except for the twinning produced by cold rolling, plastic deformation in $\beta$ phase is not found during the compression process even if DIC analysis shows that strain is accumulated in $\beta$ phase. In the $\alpha$ phase precipitates, due to the size of nanoscale, the deformation mechanisms are proved to be slips according to the SEM image and EBSD measurement in Fig. 10.

In the compression test, the specimen undergoes three states according to the stress. The first state is a stress reloading process before reaching the maximum stress of the previous cycle. The second state is a new plastic deformation (PD) process when stress reaching the maximum stress of the previous cycle but still lower than the maximum stress of the current compressing cycle. The third state is the deformation rebounding process after the stress is released. In order to investigate the continuous deformation process of Ti–12Mo alloy, AE signals released at the PD process are extracted and the AE-stress curve is established as shown in Fig. 12. From the DIC result shown in Fig. 9, strain starts to accumulate in $\beta$ twin strips as the light-yellow deformation region at cycle-4.
when cluster 3 is dominant in AE signals. Strain in $\beta$ phase keeps accumulating until the end of the compression test, which is also consistent with the AE behavior of cluster 3. Thus, strain accumulated in $\beta$ phase are assumed as the source of AE signals of cluster 3. In the cycle-6, areas with high strain in red color start to occur and concentrated on the $\alpha$ phase precipitates. In the meantime, in the stress range of 500 MPa to 600 MPa, there is a rapid rising trend in the curve of cluster 4. However, it is difficult to explain the AE behavior of cluster 4 at 200 MPa to 500 MPa since only the deformation information of the surface area can be obtained by the DIC analysis, which makes it a hard task to connect AE signals with internal deformation behaviors. From the machine learning results, it can be found that noise signals can be distinguished by k-means method, but it is still a challenge to link other AE clusters with specific deformation mechanisms.

### 4.3 Effectiveness of AE clustering for deformation analysis

By analyzing the AE behavior with deformation mechanisms in different phase, the deformation behaviors of the Mg–Y–Zn alloys can be evaluated. In this study, although 304A AE sensors are replaced as 1045S AE sensors and data used for machine learning are AE signals from the compression tests in pure magnesium and DS LPSO phase alloy in place of specific AE signals of deformation twin or kink, the machine learning results show a high level of similarity. Based on the AE behaviors, the deformation process models of the Mg$_{97}$Zn$_1$Y$_2$ alloy and Mg$_{89}$Zn$_4$Y$_7$ alloy are established as shown in Fig. 13.

For Ti–12Mo alloy, as discussed before, deformation mechanisms in $\alpha$ phase precipitates are proved to be slips while further study is required to investigate the deformation mechanisms in $\beta$ phase. Simplified deformation process schematic illustration shown in Fig. 13 is established according to DIC analysis results and the AE behavior, in which the dotted $\alpha$ phase precipitates in $\beta$ grains are not reflected. The light red and red areas indicate the degree of strain concentration according to the DIC images. Strain accumulates in $\beta$ twin strips at 400 MPa. A few slips form in $\alpha$ phase precipitates at 600 MPa. Deformed region extends and strain accumulates in $\beta$ grains at 900 MPa.

In the study of Mg–Y–Zn alloys and Ti–12Mo alloy, AE methods with different machine learning methods are applied. Method used to investigate deformation behaviors of Mg–Y–Zn alloys in this study greatly reduces the difficulty of training data acquisition and keeps good accuracy in analysis. It is verified that under the circumstance that deformation...
mechanisms have been clarified already and the AE signals of each deformation mechanism can be obtained respectively. AE method combined with the supervised machine becomes a powerful tool, with which it is possible to study deformation behaviors that are hard to investigate by direct observation or traditional detecting methods. On the contrast, to identifying the AE cluster classified by k-means in Ti–12Mo alloy, observations and DIC analyses have been made on the deformation process, but it is still a difficult task to clarify the clustering results. It is confirmed that some AE signals have similar frequency characteristic even if the sources are different, which leads to an inaccurate in clustering results and becomes the obstacles to the application of unsupervised machine learning in AE study. Thus, to achieve a better clustering with AE by unsupervised machine learning, analysis with features of AE signals except frequency spectrum combined with multiple observation methods is demanded.

5. Conclusion

In this study, the method of applying AE with supervised and unsupervised machine learning in investigating deformation behaviors of alloys with mille-feuille-like structure is evaluated. The clustering results of different machine learning methods are analyzed according to the deformation mechanisms of materials. Main results are summarized as follows.

(1) The deformation behaviors of Mg97Zn4Y2 alloy and Mg89Zn12Y2 alloy are analyzed by AE successfully. The type of AE sensor would only influence the machine learning results at a certain level. Similar results can be obtained when data used for machine learning are AE signals from the compression tests in pure magnesium and DS LPSO phase alloy in place of specific AE signals of deformation twin or kink. Behaviors of different mechanisms in α-Mg phase and LPSO phase are influenced by LPSO phase volume fraction.

(2) The deformation behaviors of Ti–12Mo alloy are investigated by AE and DIC. Strain is accumulated in β phase from 300 MPa to 400 MPa and deformation begins to concentrated on the α phase precipitates from 500 MPa to 600 MPa. Kink deformation was not observed during the compression test in Ti–12Mo alloy and the main deformation mechanisms are confirmed as slip.

(3) It is possible to analyze deformation behaviors which are hard to be investigated by traditional observation methods dynamically by AE method when deformation mechanisms have been clarified and the AE signals of each deformation mechanism can be obtained. To identify clustering results from unsupervised machine learning method, analysis with features of AE signals except frequency spectrum combined with multiple observation methods is demanded.

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